ADAMAS UNIVERSITY

SCHOOL OF BASIC AND APPLIED SCIENCES

DEPARTMENT OF MATHEMATICAL SCIENCES

Programme Name: **M.Sc. (Applied Statistics and Data Science)**

Programme Code: **MTH4203**

Programme Structure for 2-year Postgraduate Programme with EXIT Option

Academic Year: 2026-27

SCHOOL OF BASIC AND APPLIED SCIENCES

1st Year of PG Curricular Structure for 2-year PG Programmes (3+2)
M.Sc. (Applied Statistics and Data Science)

SEMESTER I

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK				REMARKS
				L	T	P	C	
1	CC	MTH421	Multivariate Calculus and Applications	3	1	0	4	
2	CC	MTH409	Optimization Techniques	3	0	2	4	
3	CC	SDS421	Advanced Regression Techniques	3	1	0	4	
4	DSE	CSE481 SDS404 SDS452	Discipline Specific Elective courses: Data Structures and Algorithm Design/ Design of Experiments/ Data Analytics for Finance SAWYAM MOOC courses approved by the department: (Any courses aligning with the themes of specified DSE courses, subject to availability in the portal within the stipulated time frame)	3 3 3	0 0 0	2 2 2	4 4 4	
5	RM	MTH450	Research Methodology	4	0	0	4	
6	SEC	SDS423	Python Programming	0	0	4	2	
7	SEC		Career Development Course I (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1	
8	AEC		Foreign Language (Select One from a basket)	2	0	0	2	
			SEMESTER CREDIT				**25**	

SEMESTER II								
SL. No.	**TYPE OF COURSE**	**COURSE CODE**	**TITLE OF THE COURSE**	**CONTACT HOURS PER WEEK**				**REMARKS**
				L	**T**	**P**	**C**	
9	CC	SDS501	Time Series Analysis	3	0	2	4	
10	CC	SDS502	Machine Learning and Applications	3	0	2	4	
11	CC	SDS503	Applied Multivariate Analysis	3	1	0	4	
12	DSE	SDS504 MTH501 SDS505	Discipline Specific Elective courses: Advanced Sampling Theory/ Matrix computation / Data Engineering SAWYAM MOOC courses (Any courses aligning with the themes of specified DSE courses, subject to availability in the portal within the stipulated time frame)	3 3 3	0 0 0	2 2 2	4 4 4	
13	MDE		To be chosen from pool of discipline specific elective courses/ elective courses of other disciplines SAWYAM MOOC courses (Any courses aligning with the themes of specified MDE courses, subject to availability in the portal within the stipulated time frame)				4	
14	SEC	CSE482	Database Management System with SQL	0	0	4	2	
15	SEC		Career Development Course II (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1	
16	AEC		Foreign Language (Select One from a basket)	2	0	0	2	
			SEMESTER CREDIT				**25**	
			TOTAL CREDIT				**50**	

Exit option with Post-Graduate Diploma after the first year or two semesters with the completion of courses equivalent to 50 credits.

2nd Year of PG Curricular Structure for 2-year PG Programmes/ One-year PG Programme after completion of Four-Year UG Programme (4+1)

PG Curricular Structure with Coursework

SEMESTER III

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK				REMARKS
				L	T	P	C	
1	CC	SDS506	Deep Learning and its Applications	3	0	2	4	
2	CC	SDS507	Survival analysis	3	1	0	4	
3	CC	SDS508	Mathematical Modelling	3	1	0	4	
4	DSE		Optional I				4	
5	MDE		To be chosen from pool of elective courses of other disciplines				4	
6	RP/ INT/ OJT	SDS553/ SDS551/ SDS552	Research Project/ Internship/ On Job Training				2	
7	SEC		Career Development Course III (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1	
			SEMESTER CREDIT				**23**	

SEMESTER IV

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK				REMARKS
				L	T	P	C	
8	CC	CSE584	Artificial Intelligence and Applications	3	0	2	4	
9	DSE		Optional II				4	
10	MDE		To be chosen from pool of elective courses of other disciplines				4	
11	ED	SDS557	Entrepreneurship Course				2	
12	Project	SDS554	Academic Project				8	
			SEMESTER CREDIT				**22**	
			TOTAL CREDIT				**45**	

2nd Year of PG Curricular Structure for 2-year PG Programmes/ One-year PG Programme after completion of Four-Year UG Programme (4+1)

PG Curricular Structure with Coursework and Research

SEMESTER III

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK				REMARKS
				L	T	P	C	
1	CC	SDS506	Deep Learning and its Applications	3	0	2	4	
2	CC	SDS507	Survival analysis	3	1	0	4	
3	DSE		Mathematical Modelling/Optional I				4	
4	CC	SDS518	Tools and Techniques for Research Writing	1	0	2	2	
5	RP/ INT/ OJT	SDS553/ SDS551/ SDS552	Research Project/ Internship/ On Job Training				2	
6	SEC		Career Development Course III (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1	
7	Research	SDS555	Dissertation Part I				6	
			SEMESTER CREDIT				**23**	

SEMESTER IV

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK				REMARKS
				L	T	P	C	
7	CC	CSE584	Artificial Intelligence and Applications	3	0	2	4	
8	DSE		Optional II				4	
10	ENT	SDS557	Entrepreneurship Course				2	
11	Project	SDS556	Dissertation Part II				12	
			SEMESTER CREDIT				**22**	
			TOTAL CREDIT				**45**	

2nd Year of PG Curricular Structure for 2-year PG Programmes/ One-year PG Programme after completion of Four-Year UG Programme (4+1)								
PG Curricular Structure with only Research								
SEMESTER III								
SL. No.	**TYPE OF COURSE**	**COURSE CODE**	**TITLE OF THE COURSE**	**CONTACT HOURS PER WEEK**				**REMARKS**
				L	**T**	**P**	**C**	
1	CC		Course related to the area identified for research				4	
2	DSE		Course related or allied to the area identified for research				4	
3	CC	SDS518	Tools and Techniques for Research Writing				2	
4	SEC		Career Development Course III (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1	
5	Research	SDS558	Dissertation Part I				12	
			SEMESTER CREDIT				**23**	
SEMESTER IV								
SL. No.	**TYPE OF COURSE**	**COURSE CODE**	**TITLE OF THE COURSE**	**CONTACT HOURS PER WEEK**				**REMARKS**
				L	**T**	**P**	**C**	
5	SEC	SDS509	Advanced data Analysis with Power BI	0	0	4	2	
6	Research	SDS559	Dissertation Part II				20	
			SEMESTER CREDIT				**22**	
			TOTAL CREDIT				**45**	

OPTIONAL PAPERS:

Students with "Only Coursework" or "Coursework and Research" are required to study **TWO** Optional Papers either from **Group A** or **Group B** during semesters III and IV. The list of the electives is given below:

List of Optional Papers				**CONTACT HOURS PER WEEK**			
Options		**Paper Name**	**Paper Code**	**L**	**T**	**P**	**C**
Optional I	**Group A**	Stochastic Process	SDS510	3	1	0	4
		Statistical Quality Control	SDS511	3	0	2	4
		Statistical Genetics	SDS512	3	1	0	4
	Group B	Cryptography and Network Security	MTH502	3	1	0	4
		Cloud Computing	CSE581	3	0	2	4
		Natural Language Processing	SDS513	3	0	2	4
Optional II	**Group A**	Reliability Theory	SDS514	3	0	2	4
		Clinical Trials and Biostatistics	SDS515	3	0	2	4
		Demography	SDS516	3	0	2	4
	Group B	Big Data Analytics	CSE582	3	0	2	4
		Cyber Security for Data Science	CSE583	3	1	0	4
		Image Processing and Computer Vision	SDS517	3	0	2	4

Note: Offering of optional papers may vary from year to year as per choice of Students or availability of resource person.

COURSE RELATED TO THE AREA IDENTIFIED FOR RESEARCH:

PG students who are eligible and interested in completing the final year of their PG program through only Research, they are required to study one Core Course (CC) from the following list, as suggested by their supervisor, based on the identified area of research.

List of Core Courses (CC) for Semester III:

Paper Name	Paper Code	L	T	P	C
Deep Learning and Applications	SDS506	3	0	2	4
Mathematical Modelling	SDS508	3	1	0	4
Survival Analysis	SDS507	3	1	0	4

Note: The offering of CC papers may vary from year to year depending on student preferences and the availability of resource persons/supervisors.

DSE:

PG students who are eligible and interested in completing the final year of their program through research are required to take one DSE course in semester III from the following list. The course should be related or allied to the area identified for research, as suggested by their supervisor.

List of DSE papers for Semester III	Paper Code	CONTACT HOURS PER WEEK			
		L	T	P	C
Stochastic Process	SDS510	3	1	0	4
Statistical Quality Control	SDS511	3	0	2	4
Statistical Genetics	SDS512	3	0	2	4
Cryptography and Network Security	MTH502	3	1	0	4
Cloud Computing	CSE581	3	0	2	4
Natural Language Processing	SDS513	3	0	2	4
Image Processing and Computer Vision	SDS517	3	0	2	4

Note: Offering of DSE papers may vary from year to year as per choice of students or availability of resource person.

List of Career Development Courses:

Course Code	Title	L	T	P	C
CLL406	Advanced Soft Skills and Aptitude I	1	0	0	1
CLL407	Advanced Soft Skills and Aptitude II	1	0	0	1
CLL503	Advanced Soft Skills and Aptitude III	1	0	0	1

List of Foreign Language Courses:

Semester	Course Code	Title	L	T	P	C
I	AEC408	French I	2	0	0	2
	AEC409	German I	2	0	0	2
	AEC410	Spanish I	2	0	0	2
II	AEC503	French II	2	0	0	2
	AEC504	German II	2	0	0	2
	AEC505	Spanish II	2	0	0	2

Adamas University
School of Basic and Applied Sciences
Department of Mathematical Sciences

Programme Structure and Syllabi
of
M.Sc. (Applied Statistics and Data Science)

Programme Structure for 2-year Postgraduate Programme
with EXIT Option

Programme Code: MTH4203
Duration: 2 Years Full Time
Academic Year: 2025-26

Vision of the University

To be an internationally recognized university through excellence in inter-disciplinary education, research and innovation, preparing socially responsible well-grounded individuals contributing to nation building.

Mission of the University

- Improve employability through futuristic curriculum and progressive pedagogy with cutting-edge technology
- Foster outcomes-based education system for continuous improvement in education, research and all allied activities
- Instil the notion of lifelong learning through culture of research and innovation
- Collaborate with industries, research centres and professional bodies to stay relevant and up-to-date
- Inculcate ethical principles and develop understanding of environmental and social realities

Core Values

- Respect
- Positivity
- Commitment
- Accountability
- Innovation

Vision of the School

To be recognized globally as a provider of education in Basic and Applied Sciences, fundamental and interdisciplinary research.

Mission of the School

- Develop solutions for the challenges in sciences through value-based science education.
- Conduct research leading to innovation in sciences.
- Nurture students into scientifically competent professionals in the usage of modern tools.
- Foster in students, a spirit of inquiry and collaboration to make them ready for careers in teaching, research and corporate world.

Vision of the Department

To create a Centre of academic excellence in Mathematics and Statistics through active teaching-learning and collaborative research

Mission of the Department

- Deliver graduates with considerable Mathematical and Statistical skills along with real-world problem-solving ability.
- Create a framework to nurture students through outcome-based education towards building a strong foundation in mathematical sciences for academia and industry.
- Conduct fundamental and cutting-edge collaborative research on mathematical and interdisciplinary fields.
- Contribute towards development of mathematical foundation in pan-university level.

Programme Educational Objectives (PEO) of M.Sc. (Applied Statistics and Data Science):

PEO 01: Graduates will equip with knowledge and understanding of statistical theory and its applications within data science.
PEO 02: Graduate will equip with the ability to implication of application in the statistical and data science field.
PEO 03: Graduates of this programme will establish as effective professionals by learning technical skills in Data Science field.
PEO 04: Students will gain proficiency in using statistical software R/Python for data science.

Programme Outcomes (POs) and Programme Specific Outcomes (PSOs) of M.Sc. (Applied Statistics and Data Science)

Students of the postgraduate programme, at the time of graduation will be able to have:

PO1	**Academic Excellence**	Understand the basic concepts, fundamental principles and the scientific theories related to Statistics and Data Science.
PO2	**Contextualized Understanding**	Ability to absorb and understand the abstract concepts that lead to various advanced theories in mathematics and Statistics.
PO3	**Research and Analysis**	Students will be acquainted with various research opportunities in the area of Statistics and Data Science both at home and abroad.
PO4	**Problem Solving Skills**	Ability in modelling and solving problems by identifying and employing the appropriate existing theories and methods.
PO5	**Modernization and Tools Usage**	Acquire the skills in handling statistical tools and programming towards problem solving and solution analysis in Data Science, AI machine and enveloping applications for real world problems.
PO6	**Societal Implication**	Understand the role of statistics in the society and apply the same to solve the real- life problems for societal and environmental concerns.
PO7	**Environment and Sustainability**	Understand the significance of preserving the environment towards sustainable development.
PO8	**Ethics**	Continue to enhance the knowledge and skills in applied statistics and data analytics for constructive activities and demonstrate highest standards of professional ethics.
PO9	**Individual and Team Work**	Use the research-based knowledge, and machine learning techniques to analyse and solve advanced problems in data sciences through individual and group projects related to the field of Statistics and data science.
PO10	**Communication**	Develop various communication skills such as reading, listening, and speaking which will help in expressing ideas and views clearly and effectively.
PO11	**Leadership Skills**	Understand the scientific and management principles and apply these to one's own work, as a member/ leader in a team to manage projects and multidisciplinary research environments.
PO12	**Life Long Learning**	Students will be proficient in statistical analysis of data, building and assessment of different statistical models, handle statistical programming software, data management and using the concepts of statistics in real life context.
PSO1		Equip graduates with analytics and problem-solving techniques.
PSO2		Graduates will get sustainable development by using mathematical and Statistical tools.
PSO3		Focus on statistical and data science and its applications.

PSO4		Graduate will Capable to design and conduct experiments, as well as analyse and interpret data.

School of Basic and Applied Sciences
Department of Mathematics

M.Sc. (Applied Statistics and Data Science)

Postgraduate Course Structure & Syllabi
Batch: 2025-2027

SCHOOL OF BASIC AND APPLIED SCIENCES

1st Year of PG Curricular Structure for 2-year PG Programmes (3+2)
M.Sc. (Applied Statistics and Data Science)

SEMESTER I

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK			
				L	T	P	C
1	CC	MTH421	Multivariate Calculus and Applications	3	1	0	4
2	CC	MTH409	Optimization Techniques	3	0	2	4
3	CC	SDS421	Advanced Regression Techniques	3	1	0	4
4	DSE	CSE481 SDS404 SDS452	Discipline Specific Elective courses: Data Structures and Algorithm Design/ Design of Experiments/ Data Analytics for Finance SAWYAM MOOC courses approved by the department: (Any courses aligning with the themes of specified DSE courses, subject to availability in the portal within the stipulated time frame)	3 3 3	0 0 0	2 2 2	4 4 4
5	RM	MTH450	Research Methodology	4	0	0	4
6	SEC	SDS423	Python Programming	0	0	4	2
7			Career Development Course I (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1
8	AEC		Foreign Language (Select One from a basket)	2	0	0	2
			SEMESTER CREDIT				**25**

SEMESTER II							
SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK			
				L	T	P	C
9	CC	SDS501	Time Series Analysis	3	0	2	4
10	CC	SDS502	Machine Learning and Applications	3	0	2	4
11	CC	SDS503	Applied Multivariate Analysis	3	1	0	4
12	DSE	SDS504 MTH501 SDS505	Discipline Specific Elective courses: Advanced Sampling Theory/ Matrix computation / Data Engineering SAWYAM MOOC courses (Any courses aligning with the themes of specified DSE courses, subject to availability in the portal within the stipulated time frame)	3 3 3	0 0 0	2 2 2	4 4 4
13	MDE		To be chosen from pool of discipline specific elective courses/ elective courses of other disciplines SAWYAM MOOC courses (Any courses aligning with the themes of specified MDE courses, subject to availability in the portal within the stipulated time frame)				4
14	SEC	CSE482	Database Management System with SQL	0	0	4	2
15	SEC		Career Development Course II (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1
16	AEC		Foreign Language (Select One from a basket)	2	0	0	2
			SEMESTER CREDIT				**25**
			TOTAL CREDIT				**50**
Exit option with Post-Graduate Diploma after the first year or two semesters with the completion of courses equivalent to 50 credits.							

2nd Year of PG Curricular Structure for 2-year PG Programmes/ One-year PG Programme after completion of Four-Year UG Programme (4+1)

PG Curricular Structure with Coursework

SEMESTER III

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK			
				L	T	P	C
1	CC	SDS506	Deep Learning and its Applications	3	0	2	4
2	CC	SDS507	Survival analysis	3	1	0	4
3	CC	SDS508	Mathematical Modelling	3	1	0	4
4	DSE		Optional I				4
5	MDE		To be chosen from pool of elective courses of other disciplines				4
6	RP/ INT/ OJT	SDS553/ SDS551/ SDS552	Research Project/ Internship/ On Job Training				2
7	SEC		Career Development Course III (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1
			SEMESTER CREDIT	**23**			

SEMESTER IV

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK			
				L	T	P	C
8	CC	CSE584	Artificial Intelligence and Applications	3	0	2	4
9	DSE		Optional II				4
10	MDE		To be chosen from pool of elective courses of other disciplines				4
11	ED	SDS557	Entrepreneurship Course				2
12	Project	SDS554	Academic Project				8
			SEMESTER CREDIT	**22**			
			TOTAL CREDIT	**45**			

2nd Year of PG Curricular Structure for 2-year PG Programmes/ One-year PG Programme after completion of Four-Year UG Programme (4+1)							
PG Curricular Structure with Coursework and Research							
SEMESTER III							
SL. No.	**TYPE OF COURSE**	**COURSE CODE**	**TITLE OF THE COURSE**	**CONTACT HOURS PER WEEK**			
				L	**T**	**P**	**C**
1	CC	SDS506	Deep Learning and its Applications	3	0	2	4
2	CC	SDS507	Survival analysis	3	1	0	4
3	DSE		Mathematical Modelling/Optional I				4
4	CC	SDS518	Tools and Techniques for Research Writing	1	0	2	2
5	RP/ INT/ OJT	SDS553/ SDS551/ SDS552	Research Project/ Internship/ On Job Training				2
6	SEC		Career Development Course III (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1
7	Research	SDS555	Dissertation Part I				6
			SEMESTER CREDIT				**23**
SEMESTER IV							
SL. No.	**TYPE OF COURSE**	**COURSE CODE**	**TITLE OF THE COURSE**	**CONTACT HOURS PER WEEK**			
				L	**T**	**P**	**C**
7	CC	CSE584	Artificial Intelligence and Applications	3	0	2	4
8	DSE		Optional II				4
10	ENT	SDS557	Entrepreneurship Course				2
11	Project	SDS556	Dissertation Part II				12
			SEMESTER CREDIT				**22**
			TOTAL CREDIT				**45**

2nd Year of PG Curricular Structure for 2-year PG Programmes/ One-year PG Programme after completion of Four-Year UG Programme (4+1)

PG Curricular Structure with only Research

SEMESTER III

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK			
				L	T	P	C
1	CC		Course related to the area identified for research				4
2	DSE		Course related or allied to the area identified for research				4
3	CC	SDS518	Tools and Techniques for Research Writing				2
4	SEC		Career Development Course III (Soft Skill / Soft Skill and Aptitude Course)	1	0	0	1
5	Research	SDS558	Dissertation Part I				12
			SEMESTER CREDIT				**23**

SEMESTER IV

SL. No.	TYPE OF COURSE	COURSE CODE	TITLE OF THE COURSE	CONTACT HOURS PER WEEK			
				L	T	P	C
5	SEC	SDS509	Advanced data Analysis with Power BI	0	0	4	2
6	Research	SDS559	Dissertation Part II				20
			SEMESTER CREDIT				**22**
			TOTAL CREDIT				**45**

OPTIONAL PAPERS:

Students with "Only Coursework" or "Coursework and Research" are required to study **TWO** Optional Papers either from **Group A** or **Group B** during semesters III and IV. The list of the electives is given below:

List of Optional Papers				**CONTACT HOURS PER WEEK**			
Options		**Paper Name**	**Paper Code**	**L**	**T**	**P**	**C**
Optional I	**Group A**	Stochastic Process	SDS510	3	1	0	4
		Statistical Quality Control	SDS511	3	0	2	4
		Statistical Genetics	SDS512	3	1	0	4
	Group B	Cryptography and Network Security	MTH502	3	1	0	4
		Cloud Computing	CSE581	3	0	2	4
		Natural Language Processing	SDS513	3	0	2	4
Optional II	**Group A**	Reliability Theory	SDS514	3	0	2	4
		Clinical Trials and Biostatistics	SDS515	3	0	2	4
		Demography	SDS516	3	0	2	4
	Group B	Big Data Analytics	CSE582	3	0	2	4
		Cyber Security for Data Science	CSE583	3	1	0	4
		Image Processing and Computer Vision	SDS517	3	0	2	4

Note: Offering of optional papers may vary from year to year as per choice of Students or availability of resource person.

COURSE RELATED TO THE AREA IDENTIFIED FOR RESEARCH:

PG students who are eligible and interested in completing the final year of their PG program through only Research, they are required to study one Core Course (CC) from the following list, as suggested by their supervisor, based on the identified area of research.

List of Core Courses (CC) for Semester III:

Paper Name	**Paper Code**	**L**	**T**	**P**	**C**
Deep Learning and Applications	SDS506	3	0	1	4
Mathematical Modelling	SDS508	3	1	0	4
Survival Analysis	SDS507	3	1	0	4

Note: The offering of CC papers may vary from year to year depending on student preferences and the availability of resource persons/supervisors.

DSE:

PG students who are eligible and interested in completing the final year of their program through research are required to take one DSE course in semester III from the following list. The course should be related or allied to the area identified for research, as suggested by their supervisor.

List of DSE papers for Semester III	Paper Code	CONTACT HOURS PER WEEK			
		L	T	P	C
Stochastic Process	SDS510	3	1	0	4
Statistical Quality Control	SDS511	3	0	2	4
Statistical Genetics	SDS512	3	0	2	4
Cryptography and Network Security	MTH502	3	1	0	4
Cloud Computing	CSE581	3	0	2	4
Natural Language Processing	SDS513	3	0	2	4
Image Processing and Computer Vision	SDS517	3	0	2	4

Note: Offering of DSE papers may vary from year to year as per choice of students or availability of resource person.

List of Career Development Courses:

Course Code	Title	L	T	P	C
CLL406	Advanced Soft Skills and Aptitude I	1	0	0	1
CLL407	Advanced Soft Skills and Aptitude II	1	0	0	1
CLL503	Advanced Soft Skills and Aptitude III	1	0	0	1

List of Foreign Language Courses:

Semester	Course Code	Title	L	T	P	C
I	AEC408	French I	2	0	0	2
	AEC409	German I	2	0	0	2
	AEC410	Spanish I	2	0	0	2
II	AEC503	French II	2	0	0	2
	AEC504	German II	2	0	0	2
	AEC505	Spanish II	2	0	0	2

Course Title	**Multivariate Calculus and Applications**
Course Code	**MTH421**
Credit	**4**
Contact Hours (L-T-P)	**3-1-0**
Course Type	**Theory**
Pre requisites	**UG Level Calculus and Probability Theory, Basic of Optimization**

Course Objectives:

The objectives of this course are as follows:

- Understand the theory behind functions of multiple variables, including limits, continuity, differentiability, and higher-order derivatives.
- Apply optimization techniques (such as Lagrange multipliers) to solve multivariable optimization problems, especially in regression and data fitting.
- Work with multivariate integrals to compute joint and marginal distributions and understand their statistical significance.
- Utilize moment generating functions to derive statistical properties and understand their role in statistical inference.
- Gain proficiency in applying multivariate calculus tools to solve practical problems in data science, machine learning, and optimization.

Course Outcomes:

On completion of this course, the students will be able to:

CO1. Recall the fundamental concepts of multivariate calculus

CO2. Explain key mathematical theories and principles of calculus and optimization and interpret their applications in statistical and data science contexts

CO3. Make use of different optimization techniques for solving real-world problem

CO4. Analyse the behaviour of multivariate functions

CO5. Evaluate the multivariate probability distributions and statistical measures in the context of data analysis and decision-making

CO6. Design and implement solutions to complex statistical problems using multivariate calculus techniques

Course Description:

This course introduces students to multivariate calculus with a focus on its applications in statistics and data science. It begins with a review of core concepts from single-variable calculus and then extends to multivariable functions. Key topics include partial derivatives, directional derivatives, critical points, local extrema, and higher-order derivatives, which are essential for optimization tasks in data science. The course covers methods for solving optimization problems, including the method of Lagrange multipliers and Hessian matrices for analyzing local maxima and minima. These techniques are applied to multivariate regression models, focusing on mean square minimization in predictive modeling. In addition, the course explores multiple integrals and their applications in multivariate probability distributions. Students will learn to compute joint, marginal, and conditional distributions, as well as concepts like covariance and correlation. The use of moment generating functions for statistical analysis will be introduced. By the end of the course, students will be equipped with the mathematical tools needed to solve complex problems in optimization, statistical modeling, and machine learning. The course provides a foundation for tackling real-world problems in data science and advanced statistical analysis.

Course Content:

Module I:

Review of single-variable calculus, Tangents, linear approximation, Critical points, local maxima and minima; Multivariable functions, Partial derivatives, Chain rule, Limit, Continuity, Differentiability, Directional derivatives, Directional ascent and descent, Tangent (hyper) plane, Linear approximation, Error, Higher order partial derivatives

Module II:

Modelling and formulation of optimization problems, Critical points - The directional of steepest ascent/descent, Hessian Matrix and local extrema, method of Lagrange multiplier, Mean square (distance) minimizations, Multivariate Regression Models

Module III:

Review of integration, Introduction to multiple integrals, Introduction to Multivariate Probability Distributions, joint, marginal, and conditional distributions, covariance, and correlation; Moment Generating Functions; Calculation and application in statistical analysis

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books

- **T1.** Apostol, T. M. (1969). Calculus (Vol. 2, 2nd ed.). Wiley.
- **T2.** Sen, A., & Srivastava, M. (1997). Regression analysis: Theory, methods, and applications. Springer.
- **T3.** Nocedal, J., & Wright, S. J. (2006). Numerical optimization (2nd ed.). Springer.

Reference Books:

- **R1.** Rice, J. A. (2007). Mathematical statistics and data analysis *(3rd ed.).* Duxbury Press.
- **R2.** Stewart, J. (2020*).* Multivariable calculus *(9th ed.). Cengage Learning.*

Course Title	**Optimization Techniques**
Course Code	**MTH409**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Basic Calculus, Linear Algebra, Programing Skill**

Course Objectives:

The objectives of this course are as follows:

- To develop the concept of unconstrained optimization problems and build up the knowledge of local and global optima
- Able to demonstrate the concept of descent methods, conjugate direction and Quasi-Newton's methods
- To acquire the knowledge of constrained optimization problems and duality

Course Outcomes:

On completion of this course, the students will be able to:

CO1: Recall and understand basic optimization concepts

CO2: Explain optimization methods for one-dimensional problems

CO3: Apply methods for multivariate optimization problems

CO4: Analyze constrained optimization problems using Lagrange and KKT conditions

CO5: Evaluate optimization techniques for unconstrained multivariate problems

CO6: Design and implement advanced optimization algorithms

Course Description:

This course provides a comprehensive overview of introduction to unconstrained and constrained optimizations. It focuses on various optimization techniques and their applications in different settings. Students will develop a deep understanding of optimization principles and strategies for solving complex real-world problems through this course. Throughout the course, practical applications and case studies related to several search techniques will be discussed to provide real-world examples of how these optimization techniques are used in decision-making processes. Students will also have the opportunity to work on assignments and projects to apply the concepts learned in the course.

Course Content:

Module I: **[22L]**

Review of Convex Sets and Convex Functions, Norms and Projections, Saddle Points;

Univariate unconstrained optimization: Fibonacci Search Method, Golden Section Method, Bisection Method, Newton-Raphson Method

Multivariate Unconstrained optimization: Random search method, Grid search method, Hooke-Jeeves pattern search method, Powell's method, Cauchy's Steepest Descent Method, Conjugate gradient Method, Newton's method, Marquardt's Method, Quasi-Newton method

Module II: [10L]

Constrained Optimization: KKT condition, Fritz John optimality condition, Quadratic programming, Wolfe's Modified Simplex Method, Sequential Quadratic Programming (SQP), Penalty function method, Barrier method

Module III: [13L]

Large-Scale and Sparse Optimization: Gradient Descent Methods, Coordinate Descent, Stochastic Gradient Descent (SGD) and Mini-batch Methods, Sparse Optimization and Compressed Sensing, Optimization in High Dimensions (curse of dimensionality, scalability), Particle Swarm Optimization (PSO)

Practical/Lab to be performed on a computer using MATLAB/Python programming:

1. Solution of unconstrained optimization problem using Fibonacci Search Method
2. Solution of unconstrained optimization problem using Golden Section Method
3. Solution of unconstrained optimization problem by Newton-Raphson Method
4. Implement Hooke-Jeeves pattern search method
5. Implement Powell's method
6. Problem based on Cauchy's Steepest Descent Method
7. Problem based on Conjugate gradient Method
8. Problem solving by Newton's method,
9. Problem based on Quasi-Newton method
10. Solution of Quadratic programming problem using Sequential Quadratic Programming (SQP)/Penalty function method
11. Particle Swarm Optimization (PSO)

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books

T1. Rao, S. S., Engineering Optimization: Theory and Practice, Fifth Edition, Wiley

T2. J. Nocedal and S.J. Wright, Numerical Optimization, Second Edition, Springer

T3. Kalyanmoy Deb, Optimization for Engineering Design-Algorithms and Examples, Second Edition, PHI Learning Private Limited, New Delhi

Reference Books

R1. D. P. Bertsekas, Nonlinear Programing, 3rd edition, Athena Scientific

R2. Hamdy A. Taha, Operations Research: An Introduction, 10th Ed., Prentice Hall India, 2017.

R3. D. Bertsimas, J. N. Tsitsiklis, Introduction to linear optimization, Athena Scientific, 1997.

R4. Kanti Swarup, P. K. Gupta and Man Mohan, Operations Research, S. Chand and Co. Pvt. Ltd.

R5. F.S. Hillier and G.J. Lieberman, Introduction to Operations Research, 11th Ed., Tata McGraw Hill, Singapore, 2020.

Course Title	**Advanced Regression Techniques**
Course Code	**SDS421**
Credit	**4**
Contact Hours (L-T-P)	**3-1-0**
Course Type	**Theory**
Pre requisites	**Linear Algebra and Linear Models**

Course Objectives:

The objectives of this course are as follows:

- To introduce the theory and applications of linear and generalized linear regression models.
- To develop understanding of the properties and assumptions of ordinary least square estimators and BLUE.
- To equip students with diagnostic tools for detecting and correcting violations in regression models.
- To enable modelling and interpretation of real-world data using linear, non-linear, and logistic regression techniques.

Course Outcomes

On completion of this course, the students will be able to

CO1. **Recall** key concepts and assumptions of linear and generalized linear models.
CO2. **Explain** the Gauss-Markov theorem and properties of OLS and BLUE.
CO3. **Apply** regression techniques to estimate and interpret model parameters.
CO4. **Analyze** residuals and diagnostics to identify model assumption violations.
CO5. **Evaluate** models using statistical tests and goodness-of-fit measures.
CO6. **Create** complete regression models with appropriate transformations and diagnostics.

Course Description:

This course provides a comprehensive understanding of linear and generalized linear models, emphasizing both theoretical foundations and practical diagnostics. It covers the core principles of Ordinary Least Squares (OLS), the Gauss-Markov theorem, and the properties of Best Linear Unbiased Estimators (BLUEs) under various assumptions. The course addresses violations of model assumptions such as autocorrelation and multicollinearity and introduces remedial measures like ridge regression. Advanced topics include multiple linear regression, non-linear models, and generalized linear models including logistic regression. Emphasis is placed on model diagnostics, interpretation, hypothesis testing, and application to real-world data.

Course Content:

Module I:

Review of Linear Models and Diagnostics: Introduction to Linear Models, Ordinary Least Squares (OLS) and their properties, Gauss-Markov theorem, estimability of linear parametric functions and their Best Linear Unbiased Estimators (BLUEs) under both uncorrelated and correlated observations. Properties of BLUEs: Properties under normality assumptions, behavior of residual sum of squares.

Regression Diagnostics: Evaluation of goodness of fit, estimation and hypothesis testing for regression parameters, residual analysis, influence of outliers, transformation of variables, confidence intervals and confidence bands for slope and intercept.

Module II:

Violation of Assumptions of BLUE: Correlated errors: detection and correction of autocorrelation, variance-covariance structure of OLS estimators, estimation of error variance under autocorrelation; Multicollinearity: detection, consequences, and correction using techniques such as ridge regression.

Module III:

Multiple Linear Regressions: Estimation and hypothesis testing for parameters, Properties of least square estimator, confidence intervals for mean, regression coefficients and predictions, collinearity, Analysis of regression residuals, check for normality of the error terms, Inverse regression, two-phase linear regression, Multiple and partial correlation coefficients.

Module IV:

Non-linear Regression: Fit of polynomial regression in one variable and several variables, Use of orthogonal polynomials, Gompertz and logistic non-linear growth models.

Module V:

Generalized Linear models and Logistic Regression: Introduction to generalized linear models, Logit transformation, logistic regression maximum likelihood estimation, Tests of hypothesis: Wald test, likelihood ratio (LR) test, score test, test for overall, Model diagnostics and interpretation of parameters.

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books:

T1. Rencher, A. C., & Schaalje, G. B. (2008). Linear models in statistics (2nd ed.). Wiley.

T2. Weisberg, S. (2014). Applied linear regression (4th ed.). Wiley.

T3. McCullagh, P., & Nelder, J. A. (1989). Generalized linear models (2nd ed.). Chapman & Hall/CRC.

Reference Books:

R1. Searle, S. R. (1971). Linear models. New York: Wiley.

R2. Seber, G. A. F., & Wild, C. J. (1989). Nonlinear regression. New York: Wiley-Interscience.

Course Title	Data Structures and Algorithm Design
Course Code	**CSE481**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Basic Mathematics and Programming Knowledge**

Course Objectives:

The objectives of this course are as follows:
To make students familiar with data structures.
To enable students to understand stack, queue, and linked list concepts.
To enhance the ability to solve real-time data problems.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Define** the concept of dynamic memory management, data types, and algorithms.
CO2: **Illustrate** advantages and disadvantages of specific algorithms and data structures.
CO3: **Solve** bugs in programs and recognize necessary operations on data structures.
CO4: **Interpret** algorithms and data structures in terms of time and memory complexity.
CO5: **Compare** the computational efficiency of key algorithms for sorting, searching, and hashing.

Course Description:

Study of advanced programming topics focused on logical structures of data as well as the design, implementation, and analysis of algorithms operating on these structures. Students will gain the fundamental concepts of data structures and understand their role in the development of efficient algorithms.

Course Content:

Module I: Introduction

Advanced concepts of pointers and dynamic memory management in C/C++. Structures and unions for complex data representation. Recursive algorithms: principles, applications, and performance analysis. Abstract Data Types (ADTs), elementary data organizations, and their design principles. Data structure operations: insertion, deletion, traversal, and their algorithmic implications. Algorithm analysis using time and space complexity. Asymptotic notations (Big O, Omega, Theta) and time-space trade-offs in algorithm selection. Advanced array topics: sparse matrices, multidimensional arrays, and memory-efficient representations. Searching techniques: linear search, binary search, and their limitations in large-scale data.

Module II: Stacks and Queues

Abstract Data Type (ADT) Stack: operations, implementation using arrays and linked lists, and applications in recursion, function call management, and syntax parsing. Advanced expression conversion and evaluation (Infix to Postfix/Prefix and vice versa), including complexity analysis and use in compilers. Abstract Data Type (ADT) Queue: implementation of Simple Queue, Circular Queue, Priority Queue, and Double-Ended Queue (Deque).

Module III: Advanced Linked Lists

Types and Variants: Singly, Doubly, Circular, and Circular Doubly Linked Lists. Advanced Structures: Multilevel linked lists. Memory Representation: Dynamic memory handling, efficient memory usage, and garbage collection techniques. Operations: Optimized traversal, insertion, deletion, and reverse operations using recursion and iteration. Applications: Implementing stacks, queues, and deques using linked structures. Polynomial arithmetic using linked lists. Real-world use cases like undo-redo functionality and memory-efficient sparse matrix representation.

Module IV: Trees and Graphs

Advanced Tree Structures: Binary Tree, Threaded Binary Tree, Binary Search Tree (BST), AVL Tree, Red-Black Tree – properties, rotations, and balancing techniques. Tree Operations: Insertion, deletion, searching, traversal (inorder, preorder, postorder) with algorithmic implementation and time complexity analysis.

Multilevel Tree Structures: B-Tree, B+ Tree – construction, insertion, deletion, applications in database indexing, and performance analysis.

Graph Theory Foundations: Terminology, types of graphs (directed, undirected, weighted), adjacency matrix and list representations.

Graph Algorithms: Depth-First Search (DFS), Breadth-First Search (BFS), Dijkstra’s algorithm, Bellman-Ford algorithm, Prim’s and Kruskal’s algorithms for Minimum Spanning Tree (MST), complexity analysis, and real-world applications.

Module V: Sorting and Hashing

Sorting: Selection, Bubble sort - Selection sort - Insertion sort - Shell sort – Radix sort. Performance analysis and comparisons. Hashing: Functions, Collisions, Collision Resolution Techniques, Separate Chaining – Open Addressing – Rehashing – Extendible Hashing.

Practical/Lab to be performed on a computer using C programming:

1. Implement array operations: insertion, deletion, searching.
2. Implement stack using arrays and linked lists.
3. Implement queue and circular queue using arrays.
4. Implement singly, doubly, and circular linked lists.
5. Write recursive functions for factorial, Fibonacci series, and Tower of Hanoi.
6. Implement sorting algorithms: Bubble, Selection, and Insertion sort.
7. Implement Merge Sort and Quick Sort with performance analysis.
8. Implement linear and binary search algorithms.
9. Create a binary search tree and perform insertion, deletion, and traversal operations.
10. Implement AVL tree and demonstrate balancing after insertions.
11. Represent graphs using adjacency matrix and list, perform BFS and DFS.
12. Implement hash tables with chaining and open addressing.
13. Implement string pattern matching using KMP or Rabin-Karp algorithms.
14. Mini project: Implement a real-world application using appropriate data structures (e.g., Student record system, Library system).

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books

T1. Lipschutz, S., & Pai, G. A. V. (2011). Data structures with C. McGraw-Hill Education.

T2. Horowitz, E., & Sahni, S. (1976). Fundamentals of data structures. Computer Science Press.

T3. Samanta, D. (2008). Classic data structures (2nd ed.). PHI Learning.

Reference Books

R1. Thareja, R. (2014). Data structures using C (2nd ed.). Oxford University Press.

R2. Weiss, M. A. (2014). Data structures and algorithm analysis in C++ (4th ed.). Pearson

Course Title	Design of Experiments
Course Code	**SDS404**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Linear Models**

Course Objectives:

The objectives of this course are as follows:

- Explore the fundamental concepts and historical context of experimental designs, including treatments, blocks, and experimental error.
- Learn to implement and analyze Completely Randomized, Randomized Block, and Latin Square Designs, including their layouts and statistical evaluations.
- Gain insights into the advantages and analysis of factorial experiments, including the design of 2^nfactorials and the concept of confounding.
- Investigate Balanced Incomplete Block Designs (BIBD), focusing on their parameters, properties, and various types, including symmetric and resolvable designs.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Recall** basic concepts and principles of experimental design.
CO2: **Analyze** CRD, RBD, and LSD, including cases with missing data.
CO3: **Apply** field experiment techniques like uniformity trials and plot layout.
CO4: **Design** factorial experiments with confounding.
CO5: **Apply** different types of BIBDs.
CO6: **Interpret** results and draw conclusions from the analysis of experimental data.

Course Description:

This course provides a comprehensive study of experimental design in agriculture, covering fundamental concepts, terminology, and historical perspectives. Students will explore various design methodologies, including completely randomized designs, factorial experiments, and incomplete block designs, with a focus on statistical analysis and practical applications in agricultural research.

Course Content:

Module I: Experimental designs

Role, historical perspective, terminology: Treatments, Experimental units & Blocks, Experimental error, Basic principles of Design of Experiments (Fisher). Uniformity trials, fertility contour maps, choice of size and shape of plots and blocks in Agricultural experiments.

Basic designs: Completely Randomized Design (CRD), Randomized Block Design (RBD), Latin Square Design (LSD) – layout, model and statistical analysis, relative efficiency, analysis with missing observations.

Module II: Factorial Experiments

Advantages, notations, and concepts, 2^2, $2^3 \ldots 2^n$ Factorial experiments, design and analysis, Total and Partial confounding for 2^n $(n \leq 5)$. Factorial experiments in a single replicate.

Module III: Incomplete Block Designs

Balanced Incomplete Block Design (BIBD) – parameters, relationships among its parameters, incidence matrix and its properties, Symmetric BIBD, Resolvable BIBD, Affine Resolvable BIBD, Intra Block analysis, complimentary BIBD, Residual BIBD, Dual BIBD, Derived BIBD.

List of experiments (to be executed using MS-Excel/R-programing)

1. Analysis of a CRD
2. Analysis of an RBD
3. Analysis of an LSD.
4. Analysis of an RBD with one missing observation
5. Analysis of an LSD with one missing observation
6. Analysis of 2^2 and 2^3 Factorial Experiments in CRD and RBD
7. Analysis of a completely confounded two-level Factorial design in 2 blocks and 4 blocks
8. Analysis of a partially confounded two-level Factorial design
9. Intra Block analysis of a BIBD
10. Construction of complimentary BIBD, Residual BIBD, Dual BIBD, Derived BIBD

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books

T1. Cochran, W. G., & Cox, G. M. (1959). Experimental design. Asia Publishing House.
T2. Das, M. N., & Giri, N. C. (1986). Design and analysis of experiments. Wiley Eastern Ltd.
T3. Gun, A. M., Gupta, M. K., & Dasgupta, B. (2008). Fundamentals of statistics (Vol. II, 9th ed.). World Press.
T4. Gupta, S. C., & Kapoor, V. K. (2008). Fundamentals of applied statistics *(4th ed.).* Sultan Chand & Sons.

Reference Books

R1. Kempthorne, O. (1965). The design and analysis of experiments. John Wiley.
R2. Montgomery, D. C. (2008). Design and analysis of experiments. John Wiley.

Course Title	**Data Analytics for Finance**
Course Code	**SDS452**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Basic Calculus, Statistics, and Programing Skill**

Course Objectives:

- Understand the fundamentals and applications of financial analytics.
- Analyze and interpret financial data using Python/R tools.
- Apply financial models for valuation, risk analysis, and forecasting.
- Develop and evaluate solutions for fraud detection and portfolio optimization.

Course Outcomes

On completion of this course, the students will be able to

CO1. **Explain** the various concept and terms in financial analytics.
CO2. **Illustrate** the wrangling process and exploratory analysis of financial data.
CO3. **Estimate** the factor beta and asset price using binomial and Black-Scholes model.
CO4. **Identify** the fraud in credit card and other financial valuations.
CO5. **Evaluate** the risk and return of a portfolio.

Course Description:

This course introduces the fundamentals of financial analytics using Python and R. It covers financial data types, data wrangling, time series analysis, and core finance concepts such as risk-return, asset valuation, and option pricing. Students will also learn to apply analytics in fraud detection, portfolio optimization, and stock return prediction using machine learning models. Practical sessions reinforce concepts through real-world financial datasets and tools

Course Content:

Module I:

Introduction to Financial Analytics: Analytics in finance, Data driven finance, relevance and scope financial analytics, recent trends in financial analytics, data in Finance: types of financial data.

Module II:

Wrangling Financial data: Reading and check financial data, managing missing data and outliers, exploratory analysis of financial data, analysis of time series data.

Module III:
Understanding basic finance using Python: Time value of money, risk and return, estimating factor betas; Asset valuation: valuing a bond, share and option; Binomial option pricing model, valuing option using Black-Scholes model, stochastics process for stock prices, implied volatility.

Module IV:
Financial fraud analytics, predicting credit card frauds, valuation analytics.

Module V:
Portfolio analytics: Return and risk of a portfolio, Markowitz Optimization process, Portfolio performance evaluation.

List of Experiments- practical to be performed on computer using R/Python:

1. Write a program to explore types of financial data and do summary statistics using a financial dataset.
2. Write a program to clean financial time series data by handling missing values and detecting outliers.
3. Write a program to perform exploratory data analysis on stock market time series data, including visualization and trend analysis.
4. Write a program to compute time value and future value, risk, and return of investments.
5. Write a program to Develop a valuation function to calculate the price and implied volatility of a European call and put option using the Black-Scholes model.
6. Write a program to build a suitable model to predict credit card frauds using suitable algorithms.
7. Write a program to estimate intrinsic stock value using regression-based valuation analytics with financial ratios.
8. Write a program to calculate portfolio return and risk using historical stock prices of selected assets.
9. Write a program to implement the Markowitz portfolio optimization model and visualize the efficient frontier.

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books

T1. Mohanty, P., (2023): Financial Analytics, Wiley India pvt. Ltd.
T2. Alexander, C. (2008). Quantitative methods in finance. Wiley.

Reference Book:

R1. Alòs, E., Merino, R. (2023): Introduction to Financial Derivatives with Python, CRC Press.
R2. Koop, G., (2006): ANALYSIS OF FINANCIAL DATA, John Wiley & Sons Ltd
R3. Skoglund, J., & Chen, W. (2015). Financial risk management: Applications in market, credit, asset and liability management and firmwide risk. John Wiley & Sons.

Course Title	**Research Methodology**
Course Code	**MTH450**
Credit	**4**
Contact Hours (L-T-P)	**3-1-0**
Course Type	**Theory**
Pre requisites	**Basic Statistics, Analytical Thinking, Research Fundamentals**

Course Objectives

To equip students with a comprehensive understanding of research methodologies to formulate effective research questions and objectives. It emphasizes the improvement of scientific writing and communication skills for creating persuasive research papers, proposals, and presentations. Students will explore ethical considerations, including the avoidance of scientific misconduct and the promotion of responsible conduct, to maintain integrity in research. Additionally, the course will focus on effectively utilizing indexing and citation databases and mastering tools for scientific writing and reference management to ensure accurate documentation of sources.

Course Outcomes

On completion of this course, the students will be able to

- **CO1.** Identify the nature and significance of several types of research, objectives for doing research.
- **CO2.** Develop skills in scientific writing and present research effectively.
- **CO3.** Apply ethical principles in research, ensuring responsible conduct and treatment of human subjects.
- **CO4.** Select the appropriate research quality journal based several criteria for publishing the research.

Course Description:

This course on research methodology covers essential concepts in research, including various approaches, ethical considerations, and the formulation of research questions. Students will learn to structure research papers, improve scientific writing, and deliver presentations. The course also addresses ethics in research, scientific misconduct, and explores indexing databases, research metrics, and tools like LaTeX for effective writing.

Course Content:

Module I: Introduction to Research Methodology:

Understanding the nature and significance of research, Different approaches to research - Basic, Applied, Interdisciplinary, Multidisciplinary, difference between quantitative and qualitative research, identifying research objectives and formulating research questions, exploring ethical considerations and responsible conduct of research.

Module II: Research Communication and Scientific Writing:

Structuring and organizing research papers and reports, enhancing scientific writing skills for research articles and proposals, preparing effective research presentations (oral and poster), developing communication skills for scientific conferences and collaborations

Module III: Ethics in Research:

Definition, moral philosophy, scientific conduct, intellectual honesty, and research integrity, scientific misconducts, falsification, fabrication and plagiarism, intellectual property rights, copyrights, Redundant publications, duplication, overlapping publications, and salami slicing, preprints (arXiv), open access.

Module IV: Research Metrices

Databases, Indexing databases, Citation databases: Web of Science, Scopus, etc. Research Metrics, Impact factor, SNIP, SJR, IPP, Cite Score, h-index, g-index, i10 index, altmetrics. Scientific writing, References and citations (Medley, Jabref)

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books

- **T1.** Bordens, K. S., & Abbott, B. B. (2025). Research design and methods: A process approach (11th ed.). McGraw-Hill.
- **T2.** Kothari, C. R., & Garg, G. (2024). Research methodology: Methods and techniques (5th ed.). New Age International Publishers.
- **T3.** Bird, A. (2006). Philosophy of science. Routledge.
- **T4.** Chaddah, P. (2018). Ethics in competitive research: Do not get scooped; do not get plagiarized.
- **T5.** Thomas, C. G. (2021). Research methodology and scientific writing. Springer Nature.

Reference Books

R1. Kumar, R. (2018). Research methodology: A step-by-step guide for beginners (5th ed.). SAGE Publications.

R2. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE Publications.

R3. Goldbort, R. (2006). Writing for science. Yale University Press.

R4. Davis, M., Davis, K. J., & Dunagan, M. (2012). Scientific papers and presentations (3rd ed.). Academic Press

Course Title	**Python Programming**
Course Code	**SDS423**
Credit	**2**
Contact Hours (L-T-P)	**0-0-4**
Course Type	**Practical**
Pre requisites	**Basic Programing knowledge**

Course Objectives:

The objectives of this course are as follows:

• To make students understand the foundational concepts of artificial intelligence and machine learning algorithms

• To enable students to implement and apply supervised, unsupervised, and deep learning models using Python

• To develop problem-solving skills by working on real-life AI/ML experiments involving classification, clustering, and detection tasks

• To analyze the performance of machine learning models using appropriate evaluation metrics and validation techniques

• To create intelligent systems for real-world applications such as face recognition, emotion detection, and voice command recognition

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Recall** fundamental Python programming concepts, including data types, control structures, functions, and object-oriented principles.

CO2: **Explain** data manipulation techniques using NumPy and pandas for efficient data analysis and preprocessing.

CO3: **Apply** data visualization tools such as matplotlib and seaborn to explore and present data insights.

CO4: **Analyze** datasets to identify patterns, trends, and relationships using statistical and machine learning methods.

CO5: **Evaluate** the performance of machine learning models using appropriate metrics like accuracy, R^2 etc.

CO6: **Create** real-world AI applications such as face recognition and voice command systems using Python and deep learning frameworks.

Course Description:

This course provides practical training in Python programming with a focus on data science and AI applications. Topics include core Python concepts, data handling with NumPy and pandas, visualization using matplotlib and seaborn, and machine learning with scikit-learn and TensorFlow/Keras.

Students will build real-world projects such as face recognition, voice command classification, and predictive models. By the end, learners will be equipped to develop data-driven and AI-powered applications using Python.

Course Content:

List of Experiments using Python

1. **Basic Python Operations and Data Types**: Perform fundamental operations including arithmetic, string manipulation, type casting, conditional statements, loops, and basic functions in Python.
2. **File Input/Output and Exception Handling**: Implement reading from and writing to text/CSV/Excel files. Handle runtime exceptions such as file not found, divide-by-zero, and type errors using try-except blocks.
3. **Object-Oriented Programming in Python**: Design and implement classes with attributes, constructors, inheritance, method overloading, and encapsulation principles in Python.
4. **NumPy Array Creation and Indexing**: Create 1D, 2D, and 3D arrays using NumPy. Perform slicing, indexing, reshaping, and broadcasting operations.
5. **Vectorized Operations and Broadcasting in NumPy**: Demonstrate speed advantages of vectorized code over loops. Perform element-wise arithmetic and broadcasting across arrays of different shapes.
6. **Statistical and Mathematical Functions in NumPy**: Apply functions like mean, median, standard deviation, and perform matrix operations including dot products and inverse.
7. **Series and DataFrame Operations with pandas**: Create Series and DataFrames, index and slice data, handle missing values, and perform basic aggregation operations.
8. **Data Cleaning and Preprocessing**: Clean raw datasets by handling missing data, removing duplicates, formatting data types, and scaling/normalizing features using pandas and scikit-learn.
9. **Data Aggregation and Grouping in Pandas**: Use groupby() for computing aggregated statistics like sum, count, mean, and creating pivot tables for analysis.
10. **Merging and Joining Data Frames**: Merge, join, and concatenate multiple datasets using Pandas functions to combine data on common columns or indices.
11. **Basic Data Visualization using Matplotlib**: Plot line graphs, bar charts, histograms, and scatter plots. Add labels, legends, and customize plots for readability.
12. **Advanced Visualization using Seaborn, Plotly**: Create complex plots such as heatmaps, pair plots, violin plots, and box plots to explore data distributions and relationships.
13. **Regression Model Building**: Implement linear regression model, evaluate using R^2 and MSE, and visualize predictions with Matplotlib, Plotly.

14. **Face Recognition Attendance System**: Build a real-time face recognition system using FaceNet embeddings, OpenCV, and Haar Cascades to log attendance based on recognized faces.
15. **Voice Command Recognition using Deep Learning**: Capture and preprocess audio input, extract MFCC features, and train a neural network to classify simple voice commands like "start", "stop", etc.

Evaluation:

Mode of Evaluation	**Practical**	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books:

T1. Ramalho, L. (2021). Fluent Python: Clear, concise, and effective programming (2nd ed.). O'Reilly Media.

T2. Goodrich, M. T., Tamassia, R., & Goldwasser, M. H. (2013). Data structures and algorithms in Python (1st ed.). Wiley.

Reference Books:

R1. Beazley, D., & Jones, B. K. (2013). Python cookbook (3rd ed.). O'Reilly Media.

R2. Slatkin, B. (2019). Effective Python: 90 specific ways to write better Python (2nd ed.). Addison-Wesley Professional.

Course Title	**Time Series Analysis**
Course Code	**SDS501**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Probability Distributions and Basic Stochastic Process, and Python Programing**

Course Objectives:

The objectives of this course are as follows:

- To make students proficient in analyzing and modeling ARMA processes.
- To enable accurate estimation and forecasting using ARMA models.
- To analyze the frequency-domain behavior of stationary time series models.
- To develop students' ability to model and forecast nonstationary time series.
- To enable students to implement robust forecasting solutions in practical scenarios.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Recall** fundamental concepts of stationary and nonstationary time series, including autocovariance functions, ARMA, ARIMA, and GARCH models.

CO2: **Explain** the theoretical properties of time series models, such as ergodicity, spectral density, and the behavior of different model components.

CO3: **Apply** core estimation techniques like Yule–Walker equations, Burg's method, and Maximum Likelihood Estimation (MLE) for time series model fitting.

CO4: **Analyze** time series data using diagnostic tools and order selection criteria (AIC, AICC, FPE) to assess model adequacy.

CO5: **Evaluate** forecasting performance using methods such as Kalman filtering, exponential smoothing, and Holt–Winters techniques in different application settings.

CO6: **Create** time series models and forecasting solutions tailored to real-world data, including financial and economic time series, by integrating appropriate modeling techniques.

Course Description:

This course provides a rigorous introduction to time series modeling and forecasting, covering stationary processes, ARMA models, and spectral analysis. Students will learn key estimation techniques (Yule–Walker, Burg's, MLE), model diagnostics, and order selection. The course also explores nonstationary and financial time series, including ARIMA, SARIMA, and GARCH models. Practical forecasting methods such as Kalman filtering, Holt–Winters, and exponential smoothing are included. Ideal for students aiming to apply time series methods in research, finance, and data science.

Course Content:

Module I: Stationary Time Series and ARMA Models

Review of Stationary Processes and Autocovariance Functions, Properties of Autocovariance and Conditions for Ergodicity, Ergodicity of WN, AR, MA, ARMA Processes, Autocovariance Generating Functions (ACGF), Introduction to ARMA (p, q) Models, Estimation of Mean and Autocorrelation, Forecasting with ARMA Models, Durbin–Levinson and Innovations Algorithms.

Module II: Spectral Analysis and Time Series Model Estimation

Spectral Representation of Stationary Processes, Spectral Density Functions and Their Properties, Spectral Densities for AR, MA, ARMA Models, Estimation Techniques for Spectral Density (including Nonparametric Methods), Core Estimation Techniques for ARMA Models (Yule–Walker, Burg's, MLE), Diagnostic Checking and Order Selection (FPE, AICC), Overview of ARIMA Model Identification and Estimation.

Module III: Nonstationary and Financial Time Series Models

Non-stationarity, Unit Root Testing, KPSS test, Forecasting Using ARIMA Models, Overview of SARIMA Models, Introduction to GARCH and Volatility Modeling (ARCH, GARCH).

Module IV: Forecasting Techniques

Kalman Filtering and Forecasting, Forecasting Techniques Viz., ARAR, Holt–Winters Methods, Exponential smoothing.

List of Experiments using Python

1. **Analysis of Stationary Time Series Models:** Generate and analyze stationary time series data, including AR, MA, and ARMA processes. Study their statistical properties such as mean, variance, and autocorrelation.
2. **Fit ARIMA Model on Real-World Data:** Perform model identification, parameter estimation, and diagnostic checking to fit ARIMA models using practical datasets.
3. **Spectral Density Estimation of AR, MA, and ARMA Models:** Compute and interpret the spectral density functions of AR, MA, and ARMA models to analyze the frequency components of time series.
4. **Fit SARIMA Models on Real-World Data:** Perform model identification, parameter estimation, and diagnostic checking to fit seasonal SARIMA models using practical datasets.
5. **Unit Root Testing and ARIMA Model Identification:** Conduct unit root tests (e.g., ADF, KPSS) to determine stationarity and identify appropriate differencing orders for ARIMA modelling.
6. **Forecasting with ARIMA and Holt–Winters Methods:** Implement forecasting techniques using ARIMA and Holt–Winters exponential smoothing methods and evaluate forecast accuracy.

7. **Volatility Modelling Using ARCH and GARCH Models:** Model and analyze financial time series volatility by fitting ARCH and GARCH models and interpreting the conditional heteroskedasticity.

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books:

T1. Brockwell, P. J., & Davis, R. A. (2002). Introduction to time series and forecasting (2nd ed.). Springer.

T2. Anderson, T. W. (1971). The statistical analysis of time series. Wiley.

Reference Books:

R1. Härdle, W. (1990). Applied nonparametric regression. Cambridge University Press.

R2. Chatfield, C. (2004). The analysis of time series: An introduction (6th ed.). Chapman & Hall/CRC.

Course Title	**Machine Learning and Applications**
Course Code	**SDS502**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Mathematics for Data Science, Programming skill**

Course Objectives:

The objectives of this course are as follows:

- To develop the student's ability to build machine learning algorithm for real life challenges.
- To educate students about different supervised and unsupervised machine learning algorithms
- To allow students to understand, interpret and process raw data

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Solve** various practical problems using **s**upervised learning algorithms

CO2: **Apply** Feature Extraction Techniques to data

CO3: **Evaluate** the various regression models and their generalization ability using bias-variance tradeoff, VC dimension.

CO4: **Develop** and implement clustering algorithms for unsupervised learning tasks

CO5: **Evaluate** error functions to assess and improve the performance of learning algorithms.

CO6: **Design** and implement reinforcement learning algorithms for decision-making tasks.

Course Description:

This course is aimed to develop a student's ability to build machine learning algorithm for real life challenges. Students will learn about different supervised and unsupervised machine learning algorithms. They will also be able to understand, interpret, and process raw data and perform feature extraction techniques.

Course Content:

Module I: Supervised Learnings

Review of Machine-learning basics and classifications algorithms: Support vector machine classifier & regression, Decision Tree classifier, Naive Bayes classifier, Ensemble learning, Bagging, Boosting, Random Forest, Improving classification with the AdaBoost algorithm

Module II: Forecasting and Learning Theory

Logistic regression, Tree-based regression, Bias/variance tradeoff, Union and Chernoff/Hoeffding bounds, Vapnik–Chervonenkis (VC) dimension

Module III: Unsupervised Learning

Grouping unlabeled items using k-means clustering, hierarchical clustering, DBScan Clustering, Association analysis with the Apriori algorithm, efficiently finding frequent itemsets with FP-growth

Module IV: Dimensionality reduction

Feature extraction – Linear Discernment Analysis, Principal component analysis, Singular value decomposition. Feature selection – feature ranking and subset selection, filter, wrapper and embedded methods. Machine Learning for Big Data: Big Data and Map Reduce

Module IV: Reinforcement learning

Markov decision process (MDP), Bellman equations, Value iteration, and policy iteration, Linear quadratic regulation, Linear Quadratic Gaussian, Q-learning, Value function approximation, reinforcement

Lab experiments to be performed using Python:

Module-I:

1. Write a Python program to classify a real-world dataset using the K-NN algorithm. Print the confusion matrix. You may use Python ML library classes.
2. Write a program to demonstrate how the ID3 algorithm works for building a decision tree. Use an appropriate dataset and classify a new sample using the generated tree.
3. Write a program to implement the Naïve Bayes classifier using a sample training dataset stored in a .csv file. Evaluate and report the classifier's accuracy using a test dataset.
4. Write a Python program to implement the Random Forest algorithm using a real-world dataset to classify a new sample using the trained model.
5. Write a program to implement the SVM classifier using a sample dataset stored in a .csv file. Evaluate and report the accuracy using test datasets.
6. Implement a non-linear Regression algorithm to fit data points. Use an appropriate dataset, draw relevant graphs, and analyse the results.
7. Implement Logistic Regression for both classification and regression tasks using suitable datasets. Draw graphs and evaluate the performance of the models.
8. Apply the Expectation-Maximization (EM) algorithm to cluster a dataset stored in a .csv file. Use the same dataset for clustering using the K-Means algorithm. Compare and comment on the quality of clustering. Use Python ML library classes if needed.

9. Apply the clustering on the appropriate DBScan Clustering algorithm. Compare and comment on the quality of clustering. Use Python ML library classes if needed.

10. Perform dimensionality reduction on a high dimensional data set using PCA.

11. Q-learning for solving GridWorld navigation problems.

Module - II

Implementation through mini project using ML Concept

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books

T1. Alpaydin, E. (2009). Introduction to machine learning (2nd ed.). MIT Press.

T2. Mitchell, T. M. (1997). Machine learning. McGraw-Hill.

T3. Harrington, P. (2012). Machine learning in action. Manning Publications Co.

T4. Bishop, C. M. (2007). Pattern recognition and machine learning. Springer.

Reference Books

R1. Bell, J. (2014). Machine learning for big data. Wiley.

R2. Shalev-Shwartz, S., & Ben-David, S. (2014). Understanding machine learning: From theory to algorithms. Cambridge University Press. Retrieved from http://www.cs.huji.ac.il/~shais/UnderstandingMachineLearning/

R3. Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: Data mining, inference, and prediction (2nd ed.). Springer. Retrieved from https://web.stanford.edu/~hastie/ElemStatLearn/

R4. Blum, A., Hopcroft, J., & Kannan, R. (2017). Foundations of data science. Retrieved from https://www.cs.cornell.edu/jeh/book.pdf

R5. Bishop, C. M. (2006). Pattern recognition and machine learning. Springer. http://www.springer.com/in/book/9780387310732

Course Title	**Applied Multivariate Analysis**
Course Code	**SDS503**
Credit	**4**
Contact Hours (L-T-P)	**3-1-0**
Course Type	**Theory**
Pre requisites	**Probability Distributions, Statistical Inference**

Course Objectives:

The objectives of this course are as follows:

- To provide a comprehensive understanding of estimation and hypothesis testing.
- To introduce multivariate statistical techniques for dimension reduction and classification.
- To enable students to analyze data using appropriate multivariate tools and software.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: Understand and apply properties of estimators, construct confidence intervals, and perform hypothesis testing.

CO2: Demonstrate knowledge of unbiased estimation, sufficiency, and large sample behavior of estimators.

CO3: Apply advanced hypothesis testing methods including likelihood ratio tests and sequential procedures.

CO4: Analyze nonparametric problems using U-statistics, rank-based tests, and goodness of fit methods.

CO5: Perform and interpret multivariate statistical methods like PCA, factor analysis, and discriminant analysis.

CO6: Implement multivariate techniques such as cluster analysis and multidimensional scaling using software tools.

Course Description:

This course covers advanced statistical methods focusing on estimation, hypothesis testing, and multivariate analysis. Students will explore properties of estimators, confidence intervals, and significance tests, including one- and two-sample tests and the Chi-square test. Topics on sufficiency, unbiased estimation, and large sample properties are also discussed. The course includes advanced hypothesis testing methods, such as likelihood-based tests and nonparametric tests. Multivariate techniques like Principal Component Analysis, Canonical Correlation Analysis, Factor Analysis, and Cluster Analysis are covered, with practical applications

Course Content:

Module 1:

Properties of estimators, confidence intervals, hypothesis testing, and significance tests, including one-sample and two-sample tests for means and variances, tests for proportions, and the Chi-square test for goodness of fit.

Module 2:

Sufficiency and completeness, unbiased estimation and bounds, equivariant estimation, large sample properties of estimators, confidence sets and intervals, Neyman–Pearson lemma and related concepts, likelihood-based tests, sequential testing, runs test for randomness, Kolmogorov–Smirnov goodness of fit test, one and two-sample U-statistics, location and scale alternatives in two-sample problem, Mann-Whitney and Mood's tests, one-way and two-way classification tests, Kruskal-Wallis and Friedman's tests, and measures of rank correlation (Spearman's rho and Kendall's tau).

Module 3:

Principal Component Analysis, Canonical Correlation Analysis, Exploratory Factor Analysis, Discriminant Analysis.

Module 4:

Multivariate Analysis of Variance (one-way), Cluster Analysis (hierarchical and K-means), Multidimensional Scaling.

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Textbooks:

T1. Casella, G., & Berger, R. L. (2002). Statistical inference (2nd ed.). Cengage Learning.
T2. Anderson, T. W. (2003). An introduction to multivariate statistical analysis (3rd ed.). Wiley.
T3. Rencher, A. C., & Christensen, W. F. (2012). Methods of multivariate analysis (3rd ed.). Wiley.

Reference Books:

R1. Lehmann, E. L., & Casella, G. (1998). Theory of point estimation (2nd ed.). Springer.
R2. Mardia, K. V., Kent, J. T., & Bibby, J. M. (1979). Multivariate analysis. Academic Press.
R3. Rao, C. R. (2002). Linear statistical inference and its applications (2nd ed.). Wiley.

Course Title	Advanced Sampling Theory
Course Code	SDS504
Credit	4
Contact Hours (L-T-P)	3-0-2
Course Type	Hybrid
Pre requisites	Sampling Theory and R programing

Course Objectives:

This course aims to provide a strong foundation in the theory and application of sampling distributions used in statistical inference. It covers univariate and multivariate sampling techniques, including estimation methods, exact distributions such as chi-square, t, and F in hypothesis testing and confidence interval construction. The course also develops practical skills in modern resampling techniques like bootstrap and jackknife.

Course Outcomes:

On completion of this course, the students will be able to:

CO1. Explain sampling distributions and techniques like transformation and generating functions.

CO2. Analyze properties and applications of χ^2, t, and F distributions in statistical inference.

CO3. Interpret the distribution of quadratic forms and results related to Fisher-Cochran's Theorem.

CO4. Evaluate estimation and inference procedure using multivariate normal and Wishart distributions.

CO5. Apply Hotelling's T^2, Mahalanobis D^2, and correlation coefficient distributions in multivariate analysis.

CO6. Implement resampling techniques such as bootstrap and jackknife for statistical estimation and inference.

Course Description:

This course covers foundational and advanced concepts in sampling theory, including exact distributions (χ^2, t, F), estimation techniques for univariate and multivariate data, and resampling methods like bootstrap and jackknife. Emphasis is placed on theoretical understanding, practical applications, and simulation-based techniques in hypothesis testing and confidence interval construction.

Course Content:

Unit I: Review of Sampling Theory

Introduction: Sampling distributions for functions of random variables –generating functions technique, transformation of variables technique with examples. χ^2 distribution, Student's t-distributions, Snedecor's F-distribution - properties, applications in hypothesis testing and confidence intervals, sampling distribution of sample mean and variance for a normal population

Unit II: Univariate and Bivariate Sampling Techniques

Non-central chi-square, t and F distributions, Distribution of X'AX, Fisher-Cochran's Theorem and related results, Random sampling from $N_P(\mu, \Sigma)$, MLE's of μ and Σ.

Unit III: Multivariate Sampling Techniques

Central Wishart distribution using Bartlett's decomposition and its properties, Distribution of Hotelling's T^2 and Mahalanobis's D^2 with applications, Distribution of sample multiple correlation coefficient, Distribution of partial correlation coefficient, Distribution of regression coefficient vector.

Unit IV: Resampling Techniques

Permutation tests, Introduction to Jackknife and Bootstrap-methods for estimating bias, standard error and distribution function based on iid random variables, Standard examples, Bootstrap confidence intervals.

List of experiments (to be executed using R-programing)

1. Simulate sampling distributions of mean and variance from a normal population.
2. Use generating functions to derive χ^2, t, and F distributions; verify with simulations.
3. Perform hypothesis tests and confidence intervals using χ^2, t, and F distributions.
4. Generate random samples from multivariate normal distribution $N_P(\mu, \Sigma)$.
5. Compute MLE of mean vector μ and covariance matrix Σ from multivariate normal samples.
6. Apply Hotelling's T^2 test and compute Mahalanobis D^2 for classification.
7. Parameter estimation using Jackknife methods and Bootstrap
8. Parameter estimation using Bootstrap methods
9. Implement bootstrap and jackknife to estimate bias, standard error, and confidence intervals.

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books

T1. Goon A.M., Gupta M.K. & Dasgupta B. (2003): An Outline of Statistical Theory, Vol I, 4th Edn., The World Press, Kolkata.

T2. Rohatgi V. K. and Saleh A.K. Md. E. (2009): An Introduction to Probability and Statistics, 2nd Edn. (Reprint), John Wiley and Sons.

T3. Gupta S. C. & Kapoor V. K. (1975): Fundamentals of Mathematical Statistics: A Modern Approach. S. Chand & Company

Reference Books

R1. Mood A.M., Graybill F.A. and Boes D.C. (2007): Introduction to the Theory of Statistics, 3rd Edn. (Reprint), Tata McGraw-Hill Pub. Co. Ltd.

R2. Hogg R.V. & Craig A.T. (1978): Introduction to Mathematical Statistics, Prentice Hall.

Course Title	**Matrix Computation**
Course Code	**MTH501**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**UG level Linear Algebra, Programing knowledge**

Course Objectives:

The objectives of this course are as follows:

- The course gives classical algorithms to solve linear system of equations by different methods, and to find the eigenvalues of a matrix.
- The course details the mathematical theory behind numerical algorithms for solving a linear system and eigenvalue problems.
- Focus on iterative methods suitable for large-scale problems arising in real-life models

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Recall** fundamental concepts of floating-point arithmetic, algorithm stability, conditioning of problems, and algorithmic complexity

CO2: **Explain** the principles behind matrix factorizations techniques and their applications to solving linear systems

CO3: **Apply** numerical methods to solve system of linear equations and compute eigenvalues and eigenvectors of matrices

CO4: **Analyze** the effects of perturbations in problems involving eigenvalues, conditioning, and sensitivity in linear systems

CO5: **Evaluate** the effectiveness and convergence of numerical algorithms

CO6: **Develop** or implement efficient numerical algorithms for solving large-scale systems and eigenvalue problems using iterative and decomposition techniques

Course Description:

Linear Algebra is one of the most widely used topics in the mathematical sciences. At under-graduate level the standard techniques for basic linear algebra tasks including the solution of linear systems, finding eigenvalues/eigenvectors and orthogonalization of bases are taught. However, these techniques are usually computationally too intensive to be used for the large matrices encountered in practical applications. Numerical linear algebra will introduce students to these practical issues and will present, analyses, and apply algorithms for these tasks which are reliable and computationally efficient.

Numerical linear algebra lab is companion course to this course in which a significant lab work using MATLAB is to be done. The theoretical material is assessed in a closed book examination.

Course Content:

Module I: Stability and Conditioning

Floating point arithmetic, Stability of algorithms, Conditioning of a problem, Perturbation analysis, algorithmic complexity

Module II: Matrix Decomposition and Solution of System of Equations

Gaussian elimination, Gaussian elimination with partial pivoting, LU factorization method for solving system of equations $Ax = b$, Cholesky decomposition - sensitivity analysis, QR factorization, Solution of $Ax = b$ Using QR Factorization, Projections Using QR Factorization, Singular value decomposition (SVD), Least-Squares Solutions to Linear Systems, normal equations, Rank deficient least-squares problems, Sensitivity analysis of least- squares problems.

Module III: Computing Eigenvalues and Eigenvectors

Localization of the Maximal Eigenvalue, matrices in super-diagonal block form, eigenvalues and eigenvectors of a few classes of nonnegative matrices; Perturbation of eigenspaces, a perturbation bound for eigenvalues. Numerical methods to compute eigenvalues and eigenvectors: the Power Method, Inverse Iteration, and the Rayleigh Quotient Iteration.

Module IV: Iterative Methods for solving system of equations

Krylov Subspace Methods for Linear Systems, Lanczos, Arnoldi, GMRES, Conjugate Gradient, and QMR.

List of experiments.

Write and execute MATLAB/Python code for the following programs:

1. LU factorization method
2. Cholesky decomposition method
3. QR factorization method
4. SVD
5. Power method
6. Inverse Iteration method
7. Rayleigh Quotient Iteration method
8. Conjugate Gradient method
9. Arnoldi Process method
10. GMRES
11. Lanczos Method

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books:

T1. Demmel, J. W. (1997). Applied numerical linear algebra. Philadelphia, PA: Society for Industrial and Applied Mathematics.

T2. Datta, B. N. (2010). Numerical linear algebra and applications (2nd ed.). Philadelphia, PA: Society for Industrial and Applied Mathematics.

Reference Books:

R1. Minc, H. (1988). Nonnegative matrices. New York, NY: John Wiley & Sons.

R2. Golub, G. H., & Van Loan, C. F. (2013). Matrix computations (4th ed.). Baltimore, MD: Johns Hopkins University Press.

R3. Trefethen, L. N., & Bau, D., III. (1997). Numerical linear algebra. Society for Industrial and Applied Mathematics.

Course Title	**Data Engineering**
Course Code	**SDS505**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Python, SQL**

Course Objectives:

The objectives of this course are as follows:

- To make students proficient in the setup and management of data infrastructure, including tools like Apache NiFi, PostgreSQL, and Elasticsearch for efficient data ingestion and processing.
- To enable learners to design, implement, and orchestrate scalable ETL pipelines using Apache Airflow, ensuring reliable and efficient data workflows.
- To develop the skills required to perform data transformation, enrichment, and exploratory analysis with Python and pandas in real-world data engineering scenarios.
- To analyze the integration of batch and real-time data processing frameworks, such as Apache Kafka and Apache Spark, to address complex data pipeline challenges.
- To develop hands-on expertise in the Hadoop ecosystem, enabling students to work with HDFS, MapReduce, and other tools to optimize distributed data processing and analytics.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Recall** the fundamental concepts of data engineering, including core tools and technologies such as Apache NiFi, PostgreSQL, and Elasticsearch.

CO2: **Explain** the process of designing and orchestrating scalable ETL pipelines using Apache Airflow, NiFi, and other data processing tools.

CO3 **Apply** data transformation, enrichment strategies, and exploratory data analysis techniques using pandas and Python in real-world data pipeline scenarios.

CO4: **Analyze** the integration of batch and stream processing frameworks (Apache Kafka and Apache Spark) for real-time data workflows.

CO5: **Evaluate** the performance and scalability of data pipelines in the Hadoop ecosystem, utilizing tools like HDFS, YARN, and MapReduce.

CO6: **Create** end-to-end production-grade data pipelines, including real-time analytics and log analysis applications using Apache HBase, Apache Sqoop, and Hive.

Course Description:

This course provides a comprehensive overview of data engineering, focusing on building scalable ETL pipelines and real-time data processing. It covers foundational tools like Apache NiFi, PostgreSQL, and Elasticsearch for data ingestion, transformation, and orchestration with Apache

Airflow. Advanced topics include batch an d stream integration using Apache Kafka and Spark, production-grade pipeline deployment, and real-time data processing. The course also explores Hadoop ecosystem components, including HDFS, MapReduce, and Apache HBase, for distributed data processing and real-time analytics. Practical applications, such as city service request data pipelines and real-time sensor data streams, are incorporated throughout.

Course Content:

Module I: Foundations of Data Engineering and ETL Pipelines

Introduction to Data Engineering and Core Responsibilities; Data Infrastructure Setup with Apache NiFi, PostgreSQL, and Elasticsearch; File Ingestion and Processing with Python and NiFi; Exploratory Data Analysis and Cleaning using pandas; Data Transformation and Enrichment Strategies; Workflow Orchestration with Apache Airflow; Designing Scalable ETL Pipelines; Application: City 311 Service Request Data Pipeline and Visualization using Kibana.

Module II: Production-Grade Pipelines and Real-Time Data Processing

Principles of Reliable and Idempotent Pipelines; Real-Time Stream Processing with Apache Kafka; Batch and Stream Integration using Apache Spark; Deploying Data Pipelines using NiFi Variable Registry; Application: Real-Time Sensor Data Stream and Production-Level Data Pipeline Deployment.

Module III: Core Hadoop Concepts and Distributed Data Processing

Introduction to Hadoop and Its Ecosystem; Hadoop Distributed File System (HDFS) Architecture and Operations; MapReduce Programming Model and Execution Flow; Resource Management and Job Scheduling with YARN; Writing and Optimizing MapReduce Jobs; Application: Large-Scale Log Analysis and Batch Data Processing Pipelines.

Module IV: High-Level Tools and Real-Time Data Workflows in Hadoop Ecosystem

Data Ingestion from External Sources using Apache Sqoop; Real-Time Read/Write Access with Apache HBase; Workflow Integration and Optimization Across the Hadoop Stack; Application: Real-Time User Event Analytics and ETL Pipeline with Hive and HBase.

List of Experiments using Python

1. **File Ingestion and Cleaning using Python, Apache NiFi, and pandas:** Implement data ingestion workflows with Apache NiFi, perform data cleaning and preprocessing using pandas for structured datasets.
2. **Exploratory Data Analysis and Transformation of City 311 Service Data:** Conduct EDA and data transformation on City 311 service datasets using Python to extract insights and prepare data for analysis.

3. **Building a Scalable ETL Pipeline with NiFi, PostgreSQL, and Elasticsearch:** Design and deploy an end-to-end ETL pipeline to extract, transform, and load data into PostgreSQL and Elasticsearch for efficient querying.
4. **Workflow Automation of ETL Tasks using Apache Airflow:** Automate ETL workflows by creating, scheduling, and managing data pipelines with Apache Airflow.
5. **Real-Time Data Stream Processing using Apache Kafka and Python:** Build real-time data streaming applications using Apache Kafka integrated with Python for data ingestion and processing.

Evaluation:

Mode of Evaluation	**Theory**		**Practical**	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Textbooks

T1. Crickard, P. (2020). Data engineering with Python. Packt Publishing.
T2. White, T. (2015). Hadoop: The definitive guide (4th ed.). O’Reilly Media.

Reference Books

R1. Kleppmann, M. (2017). Designing data-intensive applications: The big ideas behind reliable, scalable, and maintainable systems. O’Reilly Media.
R2. Kleppmann, M., & Riccomini, C. (2015). Designing data-intensive applications (2nd ed.). O’Reilly Media.

Course Title	**Database Management System with SQL**
Course Code	**CSE482**
Credit	**4**
Contact Hours (L-T-P)	**0-0-4**
Course Type	**Lab**
Pre requisites	**Fundamental Programming Concepts, Elementary Knowledge of Mathematical Logic and Data Organization**

Course Description

This course introduces the fundamentals of SQL and PL/SQL using MySQL/Oracle. Students learn to design and create databases, define constraints, manipulate data, and retrieve information using queries. The course also covers advanced features such as joins, subqueries, views, stored procedures, triggers, cursors, and transaction control. A mini project reinforces practical skills by implementing a real-world database application.

Course Outcomes

On completion of this course, the students will be able to

CO1. Demonstrate the use of SQL commands (DDL, DML, DCL, and TCL) to manage and manipulate data in relational databases.

CO2. Construct SQL queries using SELECT, WHERE, JOIN, GROUP BY, HAVING, and ORDER BY clauses to retrieve meaningful data from multiple tables

CO3. Define a commercial relational database system (Oracle, MySQL) by writing SQL using the system.

CO4. Implement views, subqueries, and set operations for advanced data retrieval and abstraction in SQL

CO5. Develop stored procedures, functions, cursors, and triggers using PL/SQL (or procedural SQL) for automating repetitive tasks and enforcing business rules.

CO6. Apply transaction control statements to demonstrate ACID properties and handle concurrent operations effectively in a multi-user environment.

Course Content

Experiment 1: Introduction to SQL & MySQL/Oracle.

Experiment 2: Creating Databases & Tables, Data Types and Constraints (Primary Key, Foreign Key, Unique, Check, Not Null)

Experiment 3: Insertion, Updation, and Deletion of tuples. Simple Queries using SELECT, WHERE, ORDER BY, BETWEEN, LIKE.

Experiment 4: Aggregate Functions: COUNT, SUM, AVG, MIN, MAX.GROUP BY, HAVING Clauses

Experiment 5: Performing joining operations. INNER JOIN, LEFT JOIN, RIGHT JOIN, FULL JOIN

Experiment 6: Nested Queries and Correlated Subqueries

Experiment 7: Creating and Using Views
Experiment 8: Introduction to PL/SQL
Experiment 9: Creating and Using Stored Procedures
Experiment 10: Creating and Using Triggers. Cursor and Exception Handling
Experiment 11: Transaction Control Commands (COMMIT, ROLLBACK, SAVEPOINT)

Mini Project:
Design and implement a mini database project (e.g., Library System, Hospital Database, Student Attendance System) using SQL and front-end tools (optional).

Evaluation:

Mode of Evaluation	**Practical**	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Textbooks

T1. Bayross, E. . SQL, PL/SQL: The programming language of Oracle. BPB Publications.
T2. Silberschatz, A., Korth, H. F., & Sudarshan, S. (2019). Database system concepts (7th ed.). McGraw-Hill.
T3. Ullman, J. D. (1988). Principles of database and knowledge-base systems (Vol. 1). Computer Science Press.

Reference Books:

R1. Elmasri, R., & Navathe, S. B. (2021). Fundamentals of database systems (7th ed.). Pearson Education.
R2. Abiteboul, S., Hull, R., & Vianu, V. (1995). Foundations of databases. Addison-Wesley.

Course Title	**Deep Learning and Applications**
Course Code	**SDS506**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Machine Learning and Programing**

Course Objectives:

The objective of the course is to equip students with a comprehensive understanding of deep learning techniques and their practical applications across various fields.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Explain** the basic concepts of neural networks, perceptrons, activation functions, and loss functions, and demonstrate their role in deep learning models.

CO2: **Apply** convolution NN and analyze the performance of various ConvNet architectures such as AlexNet, VGG, ResNet, and MobileNet.

CO3: **Implement** object detection and segmentation algorithms, and evaluate deep learning approaches using appropriate datasets and performance metrics.

CO4: **Develop** sequence models using RNNs, LSTMs, and word embeddings to solve language and sequential data problems.

CO5: **Examine** the integration of vision and language tasks (e.g., image captioning) and assess the importance of explainability and bias in deep learning models.

CO6: **Formulate** and implement a complete deep learning solution to a real-world problem, including model selection, training, optimization, and empirical validation through a mini-project.

Course Description:

The course offers a comprehensive exploration of deep learning techniques and their transformative impact across various domains. Designed for students with a foundational understanding of machine learning, this course delves into the architectures, algorithms, and tools that drive deep learning innovations. This course aims to equip students with both theoretical knowledge and practical skills, preparing them for careers in data science, artificial intelligence, and related fields. By the end of the course, participants will have a solid foundation in deep learning and its applications, ready to tackle complex challenges in various industries.

Course Content:

Module I:

Neural Networks: Basic concepts of artificial neurons, single and multi-layer perceptron, perceptron learning algorithm, its convergence proof, different activation functions, SoftMax cross entropy loss function.

Convolutional Neural Networks: Basic concepts of Convolutional Neural Networks starting from filtering, Convolution and pooling operation and arithmetic of these.

ConvNet Architectures: Discussions on famous Convnet architectures - AlexNet, ZFNet, VGG, C3D, GoogLeNet, ResNet, MobileNet-v1.

Regularization, Batchnorm: Discussion on regularization, Dropout, Batchnorm, momentum, RMS prop, Adam's optimization algorithm, Learning rate decay, etc.

Module II:

Detection, Segmentation: Discussion on detection, segmentation problem definition, challenges, Evaluation, Datasets and Localization by regression, Discussion on detection as classification, region proposals, RCNN architectures.

Recurrent Neural Networks: Discussion on Recurrent Neural Networks (RNNs), Long-Short Term Memory (LSTM) architectures, and basics of word embedding

Module III:

Vision and Language: Discussion on different tasks involving Vision and Language e.g., Image and video captioning along with the use of attention and broad discussion about application areas.

Explainability and Bias: Discussion on explainability and bias in Deep Learning system. The need for explanation, introspection vs justification, activation maximization and activation map-based explanation generation, Black-box explanation generation, etc., Bias in AI and in image captioning tasks

Module IV:

Implantation (through mini project) of deep learning concepts: Complete a Deep Learning solution to a problem, starting from problem formulation, appropriate algorithm selection and implementation, and empirical study into the effectiveness of the solution

List of experiments using Python

1. Implement a neural network model for handwritten digit recognition on the MNIST dataset and evaluate its performance using accuracy and loss metrics.
2. Design and train a Convolutional Neural Network (CNN) to classify images of cats and

dogs

3. Implement an LSTM-based recurrent neural network to perform sentiment analysis on IMDB movie review data, and evaluate model performance using precision, recall, and F1-score.
4. Develop a deep learning model to detect face masks in real-time using CNN integrated with OpenCV for live video stream processing.
5. Apply transfer learning with the MobileNet architecture to classify different types of fruits from image datasets, and compare results with a simple CNN baseline.
6. Implement a CNN model to detect and classify the color of traffic lights (red, yellow, green) from images, and test the system's accuracy on real-world samples.
7. Design and implement a real-time emotion recognition system using a deep learning model with webcam input, classifying facial expressions into multiple emotion categories.
8. Image Caption Generator Using Pretrained CNN and RNN

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books:

T1. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning* (1st ed.). MIT Press. http://www.deeplearningbook.org/

T2. Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks, 61*, 85–117. https://arxiv.org/abs/1404.7828

Web References:

R1. http://neuralnetworksanddeeplearning.com/chap4.html

R2. https://www.utdallas.edu/~herve/abdi-awPCA2010.pdf

R3. https://www.cs.princeton.edu/picasso/mats/PCA-Tutorial-Intuition_jp.pdf

R4. http://www-users.math.umn.edu/~lerman/math5467/svd.pdf

Course Title	Survival Analysis
Course Code	SDS507
Credit	4
Contact Hours (L-T-P)	3-1-0
Course Type	Theory
Pre requisites	Probability Theory and Distribution

Course Objectives:

The objectives of this course are as follows:

- To introduce fundamental concepts related to time-to-event data and survival functions
- To enable students to work with censored and truncated survival data
- To develop skills in nonparametric and parametric estimation of survival functions
- To equip students with knowledge of regression models including Cox proportional hazards model
- To enable students to interpret survival outcomes and conduct comparison between survival curves

Course Outcomes:

On completion of this course, the students will be able to:

CO1: Define key concepts in survival analysis including censoring, truncation, survival, and hazard functions

CO2: Summarize survival data and estimate survival curves using Kaplan-Meier and life table methods

CO3: Compare survival distributions between groups using log-rank and Wilcoxon tests

CO4: Apply parametric survival models such as exponential, Weibull, and log-normal to estimate and interpret model parameters

CO5: Construct Cox proportional hazards regression models and assess their assumptions

CO6: Analyze time-to-event data from real-world applications and draw valid conclusions from statistical models

Course Description:

This course provides an in-depth study of the statistical methods used for analyzing survival data, focusing on time-to-event outcomes. Students will learn to handle censored and truncated data, estimate survival, and hazard functions, and compare survival experiences across groups. Both nonparametric and parametric approaches are covered, along with semi-parametric models like the Cox model, widely used in biostatistics, medical research, and reliability engineering.

Course Content:

Module I:

Basic concepts: survival time, censoring, truncation, survival function, hazard function, cumulative hazard, relationship between survival and hazard functions, types of censoring: right, left, and interval censoring, examples and graphical presentation of survival data

Module II:

Nonparametric estimation: Kaplan-Meier estimator, life-table method, estimation of survival probabilities, comparing survival distributions: log-rank test, Wilcoxon test, graphical comparison of survival curves, median survival time, confidence intervals

Module III:

Parametric survival distributions: exponential, Weibull, log-normal, log-logistic, gamma, probability plots and hazard plots, parameter estimation using maximum likelihood, goodness-of-fit and model selection: AIC, BIC, likelihood ratio test for model comparison

Module IV:

Cox proportional hazards model: assumptions, estimation using partial likelihood, interpretation of hazard ratios, model diagnostics and checking proportional hazards assumption, time-dependent covariates, stratified Cox model, Competing risks and recurrent event models

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books:

T1. Kleinbaum, D. G., & Klein, M. (2012). Survival analysis: A self-learning text (3rd ed.). Springer.

T2. Klein, J. P., & Moeschberger, M. L. (2003). *Survival analysis: techniques for censored and truncated data* (Vol. 1230). New York: Springer.

Reference Books:

R1. Miller Jr, R. G. (2011). Survival analysis. John Wiley & Sons.

R2. Lee, E. T., & Wang, J. W. (2013). Statistical methods for survival data analysis (4th ed.). Wiley.

Course Title	**Mathematical Modelling**
Course Code	**SDS508**
Credit	**4**
Contact Hours (L-T-P)	**3-1-0**
Course Type	**Theory**
Pre requisites	**Differential Equations**

Course Objectives:

The course aims to provide foundational knowledge of empirical and mechanistic models with a focus on nonlinear growth and ecological interaction models. It emphasizes parameter estimation techniques and the analysis of two-species systems. Students will also learn compartmental modeling and practical data fitting for biological and environmental applications.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Explain** difference between empirical and mechanistic models.

CO2: **Apply** nonlinear growth models like logistic, Gompertz, and Richards in biological contexts.

CO3: **Estimate** parameters in nonlinear models using methods such as linearization and Levenberg-Marquardt.

CO4: **Analyze** two-species systems using models like Lotka-Volterra and Gause's competition model.

CO5: **Develop** and interpret compartmental models for dynamic biological systems.

CO6: **Construct** the mechanistic nonlinear models to real-world data

Course Description:

This course explores empirical and mechanistic models with a focus on nonlinear growth models such as monomolecular, logistic, Gompertz, and Richards, and their applications in agriculture and fisheries. It includes nonlinear estimation techniques, predator-prey dynamics, and compartmental modeling. Emphasis is placed on both theoretical modeling and practical data fitting in biological and ecological systems.

Course Content:

Module I:

Empirical and mechanistic models, nonlinear growth models like monomolecular, logistic, Gompertz, Richards, applications in agriculture and fisheries

Module II:

Nonlinear estimation: Least squares for nonlinear models, methods for estimation of parameters like Linearization, Steepest, and Levenberg Marquardt's Reparameterization

Module III:

Two-species systems, Lotka-Volterra model, Leslie-Gower and Holling-Tanner: nonlinear preypredator models, Volterra's principle and its applications, Gause competition model

Module IV:

Compartmental modelling - First and second-order input-output systems, Dynamics of a multivariable system, Practical Fitting of mechanistic nonlinear models, Application of Schaefer and Fox nonlinear models, Fitting of compartmental models.

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books

T1. Draper, N. R., & Smith, H. (1998). Applied regression analysis (3rd ed.). John Wiley & Sons

T2. Efromovich, S. (1999). Nonparametric curve estimation: Methods, theory, and applications. Springer.

Reference Books

R1. Ratkowsky, D. A. (1983). Nonlinear regression modelling: A unified practical approach. Marcel Dekker.

R2. Seber, G. A. F., & Wild, C. J. (1989). Nonlinear regression. John Wiley & Sons.

Course Title	**Artificial Intelligence and Applications**
Course Code	**CSE584**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Probability Basics, Basic Programming, Data Structures, Discrete Mathematics**

Course Objectives:

- To provide the most fundamental knowledge of AI.
- To make a computer that can learn, plan, and solve problems autonomously.
- To give the students a perspective on the main research topics in AI, i.e., problem solving, reasoning, planning, etc.
- To enable students to acquire knowledge on some basic search algorithms for problem solving, knowledge representation, and reasoning.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Recall** the history of Artificial Intelligence and learn real-world AI applications through case studies.

CO2: **Apply** uninformed and informed search strategies (DFS, BFS, Hill-climbing, GA, etc.) to solve general problem-solving tasks.

CO3: **Examine** logic and reasoning methods from a computational perspective

CO4: **Design** planning solutions using state-space search, planning graphs, and propositional logic, and compare heuristic-based approaches for efficiency.

CO5: **Illustrate** probabilistic reasoning using Bayesian networks and justify decisions under uncertainty with probability-based models.

CO6: **Use** the concepts of AI in various fields.

Course Description:

This course provides a comprehensive introduction to the foundational concepts and advanced techniques in Artificial Intelligence (AI). It covers the history and evolution of AI, equipping students with a strong understanding of how AI applications are developed and evaluated in real-world scenarios. The course explores various AI methodologies, including problem-solving, search algorithms, knowledge representation, and decision-making under uncertainty. Students will dive into AI's essential components, such as heuristic search strategies, adversarial search in games, and constraint satisfaction problems. They will also explore knowledge-based systems, propositional and first-order logic, and inference mechanisms that form the backbone of intelligent agents. The course emphasizes planning algorithms, probabilistic reasoning, and handling uncertainty in AI, with a focus on Bayesian networks. Practical applications include computer vision, image processing, natural language understanding, and interaction, with deep learning approaches and pre-trained models integrated into case studies. In the final module, students apply AI principles through a hands-on mini-project, where they implement and showcase their understanding of key AI concepts. Upon completion, students will be well-prepared to design, analyze, and apply AI techniques to a variety of complex problems in modern technology and industry.

Course Content:

Module I:

Introduction to artificial intelligence: History of AI, Proposing and evaluating AI applications, Any Case study

Module II:

Problem Solving, Search and Control Strategies: General problem solving, production systems, control strategies forward and backward chaining, exhaustive searches depth first breadth-first search, Search Techniques: Informed (Heuristic) Search and Exploration, Greedy best-first search, A* search, Memory bounded heuristic search, Heuristic functions, inventing admissible heuristic functions, Local Search algorithms, Hill-climbing, Simulated Annealing, Genetic Algorithms, Online search Constraint Satisfaction Problems, Backtracking Search, variable and value ordering, constraint propagation, intelligent backtracking, local search for CSPs, Adversarial Search, Games, The minimax algorithm, Alpha-Beta pruning, Imperfect Real-Time Decisions, Games that include an Element of Chance

Module III:

Knowledge Representations: Knowledge Based Agents, Logic, Propositional Logic, Inference, Equivalence, Validity and Satisfiability, Resolution, Forward and Backward Chaining, DPLL algorithm, Local search algorithms, First Order Logic, Models for first-order logic, Symbols and Interpretations, Terms, Atomic sentences, complex sentences, Quantifiers, Inference in FOL, Unification and Lifting, Forward Chaining, Backward Chaining, Resolution

Module IV:

Planning, Language of planning problems: Planning with state-space search, forward and backward state-space search, Heuristics for state-space search, partial order planning, planning graphs, planning with propositional logic. Uncertainty, Handing uncertain knowledge, rational decisions, basics of probability, axioms of probability, inference using full joint distributions, independence, Baye‘s Rule and conditional independence, Bayesian networks, Semantics of Bayesian networks, Exact and Approximate inference in Bayesian Networks

Module V:

Applications: various wings of AI–Neurophysiology, cognitive science, pattern recognition, machine learning, machine vision, linguistics, data science, robotics, bioinformatics, speech processing, generative systems, Q&A, Tutorial 5

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books

T1. S Russell & P Norvig, Artificial Intelligence: A Modern Approach, Prentice-Hall, 2010.

T2. Elaine Rich and Kevin Knight, Artificial Intelligence, Tata McGraw-Hill.

T3. Dan W. Patterson, Introduction to Artificial Intelligence and Expert Systems, Prentice Hall.

Reference Books:

R1. Nils J. Nilson, Principles of Artificial Intelligence, Narosa Publishing House.

R2. Clocksin & C S Melish, Programming in PROLOG, Narosa Publishing House.

R3. M Sasikumar, S Ramani, Rule-based Expert System, Narosa Publishing House.

R4. Nils J. Nilsson, Artificial Intelligence: A New Synthesis, Morgan Kauffman, (Harcourt Asia), 2002.

R5. AI on the Web [http://www.cs.berkeley.edu/~russell/ai.html]

R6. http://www.aaai.org

Course Title	Tools and Techniques for Research Writing
Course Code	**SDS518**
Credit	**2**
Contact Hours (L-T-P)	**1-0-2**
Course Type	**Hybrid**
Prerequisite:	**Basic knowledge of research methodology, academic writing**

Course Objectives:

The objectives of this course are as follows:

- Understand the structure and purpose of LaTeX
- Create professional documents using LaTeX
- Format text, lists, tables, and include mathematical expressions
- Manage references, bibliographies, and figures
- Use LaTeX for academic and technical writing.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Demonstrate** familiarity with the basic structure and commands of a LaTeX document, including document classes, packages, and environments.

CO2: **Organize** a well-structured document with properly formatted text, lists, tables, and figures suitable for academic and technical writing.

CO3: **Apply** LaTeX math mode to accurately represent mathematical expressions, equations, and symbols.

CO4: **Organize** and manage citations and references using LaTeX tools such as BibTeX or BibLaTeX, and create cross-referenced documents.

Course Content:

Module I:

Introduction and basic document structure, Introduction to Latex, Structure of a LaTeX document, Sections, paragraphs, and formatting text, Compiling and debugging LaTeX documents. List structures: Itemize, enumerate, description

Module II:

Symbols and Fonts: Greek letters, symbols, and operators, superscripts, subscripts, fractions, roots, integral, differential, Bold fonts, emphasise, mathbf, mathcal etc. Changing sizes Large, Larger, Huge, tiny

Tables and Figures: Creating tables with different alignments, placement of horizontal, vertical lines. Changing and placing the figures, alignments

Module III:
Mathematical Equations writing, piecewise function, matrices, trigonometric, logarithmic, exponential functions, line, surface, volume integrals

Writing Projects: Different type of document classes, e.g., article, report, book, beamer etc. Using packages and customizing documents, Page Layout: Titles, Abstract, Chapters, Sections, subsections, paragraph, verbatim, References, Equation references, citation.
Plagiarism: An overview of plagiarism. plagiarism checking and corrections

List of Practical:
The following topics will be learned through practical using various Latex software, e.g., TeX Live / MiKTeX / Overleaf.

1. Installing LaTeX (TeX Live / MiKTeX / Overleaf).
2. Write a mathematical expression.
3. Report writing on a practical done in laboratory with results, tables and graphs.
4. Write a well-organized article using overleaf.
5. How to check plagiarism using various software, e.g., Copyscape, Quetext, Unicheck, Turnitin, and PlagScan.
6. Sample Research article writing using Latex
7. Sample book chapter writing using Latex

Text Books:

T1. Lamport, L. (1994). LaTeX: A document preparation system: User's guide and reference manual (2nd ed.). Addison-Wesley Professional. \
T2. Krishnan, E. (Ed.). (2020). The LaTeX tutorial: A primer (Rev. ed.). Sayahna Foundation.

Reference Books:

R1. Mittelbach, F., & Fischer, U. (2023). The LaTeX companion (3rd ed.). Addison-Wesley Professional.
R2. Grätzer, G. (2024). Text and math into LaTeX (6th ed.). Springer.

Course Title	**Advanced Data Analysis with Power BI**
Course Code	**SDS509**
Credit	**2**
Contact Hours (L-T-P)	**0-0-4**
Course Type	**Practical**
Prerequisite	**Basic Computer Skills and Microsoft Excel**

Course Objectives:

This course aims to provide advanced knowledge and practical skills in data visualization, data modeling, and business intelligence using Power BI. Students will learn to connect, transform, and analyze data from various sources, creating interactive dashboards and reports. The course also emphasizes the application of DAX, Power Query, and integration with external tools for comprehensive data analysis.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: **Understand** the fundamentals of Power BI and process the data from various sources.
CO2: **Create** various visualizations and interactive dashboards for data presentation.
CO3: **Develop** the data models using DAX for new measures.
CO4: **Apply** Power Query for data transformation and enhance reports with custom visuals.
CO5: **Analyze** the data effectively using Power BI's visualization and modeling capabilities.
CO6: **Utilize** advanced Power BI features and integrate it with other tools.

Course Description:

This course provides a comprehensive introduction to Power BI, focusing on business intelligence and data visualization techniques. Students will learn how to connect to various data sources, create dynamic visualizations, and design interactive dashboards. The course covers data modeling and DAX functions for performing advanced analytics, along with hands-on case studies. Additionally, students will explore Power Query, M Language, and integration with other tools like Excel and Azure for enhanced reporting capabilities.

Course Content:

Unit 1: Introduction to Power BI:

Introduction to Power BI; Understanding Business Intelligence Concepts and the Role of Power BI; Installation and Configuration of Power BI Desktop; Overview of Power BI Desktop Interface; Exploring Power BI File Formats (.pbix, .pbit); Connecting to Different Data Sources (Excel, CSV, SQL Server, Web); Techniques for Importing and Loading Data.

Unit 2: Data Visualization Techniques:
Introduction to Various Visualization Types; Developing Basic Visualizations (Bar, Line, Pie Charts, etc.); Visual Formatting and Customization Techniques; Implementation of Slicers and Filters; Building and Customizing Tables and Matrices; Visualizing Data Using Maps and Geographic Tools; Crafting Interactive and Dynamic Dashboards.

Unit 3: Data Modeling and DAX:
Basics of Data Modeling; Establishing and Managing Relationships between Tables; Introduction to DAX (Data Analysis Expressions); Creating Calculated Columns and Measures; Applying Basic DAX Functions (SUM, AVERAGE, COUNT, etc.); Working with Advanced DAX Functions (CALCULATE, FILTER, ALL, etc.); Utilizing Time Intelligence Functions (YEAR, MONTH, QUARTER, etc.).

Unit 4: Advanced Features and Case Studies:
Exploring Power Query and Basics of M Language; Integration of Power BI with External Tools (Excel, Azure, etc.); Working with Custom Visuals and Accessing the Marketplace; Case Study on Dashboard Development; Presentation and Reporting through Power BI.

List of experiments (to be executed using Power BI):

1. Import datasets from Excel, CSV files, and SQL Server into Power BI, and demonstrate understanding of various data loading techniques.
2. Utilize the Query Editor to perform data cleaning and transformation operations, including the removal of duplicate records and management of missing data.
3. Construct basic visualizations such as bar charts, line graphs, and pie charts, with emphasis on formatting and customization for enhanced clarity.
4. Design and develop interactive dashboards by applying slicers, filters, and a variety of visualization types, adhering to best practices in data presentation.
5. Integrate and visualize geographic data within Power BI through the creation of map-based visualizations for spatial data analysis.
6. Build comprehensive data models by establishing and managing relationships among multiple tables, with a focus on understanding primary and foreign key concepts.
7. Create calculated columns and measures using fundamental DAX functions including SUM, AVERAGE, and COUNT.
8. Apply advanced DAX functions such as CALCULATE, FILTER, and time intelligence functions to execute complex analytical computations.
9. Integrate Power BI with external tools such as Excel to augment data analysis processes and optimize workflow efficiency.
10. Explore and implement custom visuals from the Power BI Marketplace to enhance the richness and effectiveness of data representation.

11. Design and present a compelling dashboard project utilizing real-world datasets, demonstrating applied knowledge of data analysis and visualization techniques.

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books:

T1. Ferrari, A., & Russo, M. (2016). Introducing Microsoft Power BI. *Microsoft Press.*

T2. Machiraju, S., & Gaurav, S. (2018). Power BI data analysis and visualization. *De Gruyter.*

T3. Mihiranga, N. (2022). Power BI data modeling: Build interactive visualizations, learn DAX, Power Query, and develop BI models. *BPB Publications.*

Reference Books:

R1. Russo, M., & Ferrari, A. (2019). The definitive guide to DAX: Business intelligence for Microsoft Power BI, SQL Server Analysis Services, and Excel *(2nd ed.).* Microsoft Press.

R2. Gunnarsson, Á., & Johnson, M. (2020). Pro Microsoft Power BI administration: Creating a consistent, compliant, and secure corporate platform for business intelligence *(1st ed.).* Apress.

Course Title	**Stochastic Process**
Course Code	**SDS510**
Credit	**4**
Contact Hours (L-T-P)	**3-1-0**
Course Type	**Theory**
Pre requisites	**Probability Theory and Distributions**

Course Objectives:

- To understand the basic components of stochastic process
- To build the knowledge about discrete-time and continuous-time Markov chain
- To understand different Queuing model
- To build the knowledge about Martingales, Brownian motion, Renewal process and Branching process

Course Outcomes:
On completion of this course, the students will be able to:

CO1. **Recall** basic concepts of probability theory and stochastic processes
CO2. **Explain** the Markov chains and their applications
CO3. **Apply** Markov chains to solve queueing and communication system problems
CO4. **Evaluate** the properties of Brownian motion, renewal processes, and branching processes.
CO5. **Interpret** the behaviour of Markov regenerative processes and branching processes
CO6. **Analyse** complex real-world problems using stochastic processes

Course Description:
This course offers a deep dive into stochastic processes, focusing on the key mathematical and probabilistic concepts needed to model and analyse random systems over time. Students will review core probability theory—random variables, distributions, and generating functions before studying types and classifications of stochastic processes. The course covers Discrete-time and Continuous-time Markov Chains, along with advanced topics like Martingales, Renewal, and Branching Processes. By the end, students will be able to apply these models to real-world systems in fields like operations research, networks, finance, and engineering.

Course Content:
Module-I
Review of probability theory, random variable and distribution; Probability generating function and its properties, Sequence of random variables; Simple stochastic process: Definition, classification and Examples.

Module-II
Discrete-time Markov chains: Introduction, Definition and Transition Probability Matrix, Chapman-Kolmogorov Equations, Classification of States, Limiting and Stationary Distributions, Ergodicity, Time Reversible Markov Chain, Application of Irreducible Markov chains in Queuing Models; Reducible Markov Chains.

Module -III

Continuous-time Markov chains: Definition, Kolmogorov Differential Equation and Infinitesimal Generator Matrix, Limiting and Stationary Distributions, Birth and Death Processes, Poisson processes, M/M/1 Queuing model; Simple Markovian Queuing, Applications of Continuous-time Markov chain, Queueing networks, Communication systems, Stochastic Petri Nets

Module -IV

Martingales: Conditional expectations, definition and examples of martingales, inequality, convergence and smoothing properties

Brownian motion: Definition and Properties; Processes Derived from Brownian motion, Stochastic Differential Equation

Renewal Processes: Renewal Function and Equation, Generalized Renewal Processes and Renewal Limit Theorems, Markov Renewal and Markov Regenerative Processes, Non-Markovian Queues, Application of Markov Regenerative Processes

Branching Processes: Definition and examples branching processes, probability generating function, mean and variance, Galton-Watson branching process, probability of extinction

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books

- **T1.** Medhi, J. (2001). Stochastic processes (2nd ed.). New Age International (P) Ltd.
- **T2.** Ross, S. M. (1996). Stochastic processes (2nd ed., WSE edition). Wiley.

Reference Books

- **R1.** Taylor, H. M., & Karlin, S. (1998). An introduction to stochastic modeling (3rd ed.). Academic Press.
- **R2.** Blanco Castañeda, L., Arunachalam, V., & Dharmaraja, S. (2012). Introduction to probability and stochastic processes with applications. Wiley.
- **R3.** Grimmett, G. R., & Stirzaker, D. R. (2001). Probability and random processes (3rd ed.). Oxford University Press.

Course Title	**Statistical Quality Control**
Course Code	**SDS511**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Descriptive Statistics, Hypothesis Testing, Programming skill**

Course Objectives:

The objectives of this course are as follows:

- To provide foundational understanding of acceptance sampling methods and their theoretical basis.
- To explore attribute and variable sampling plans, their construction, and performance evaluation.
- To enable students to use quality control techniques effectively using standard procedures and software tools.

Course Outcomes:

On completion of this course, the students will be able to:

CO1. **Explain** foundational concepts of Statistical Quality Control and basic control charts for variables and attributes.

CO2. **Apply** advanced process monitoring techniques including CUSUM, EWMA, multivariate charts, and methods for short runs and autocorrelated data.

CO3. **Design** and implement acceptance sampling plans and apply Reliability Engineering concepts.

CO4. **Utilize** Taguchi methods, QFD, Kaizen, Benchmarking, Lean Management, and 5S for quality improvement.

CO5. **Integrate** SQC tools for real-world process analysis and improvement projects.

CO6. **Analyze** emerging trends in quality management and Industry 4.0 applications.

Course Description:

This course provides an in-depth study of the statistical methods used for analyzing survival data, focusing on time-to-event outcomes. Students will learn to handle censored and truncated data, estimate survival, and hazard functions, and compare survival experiences across groups. Both nonparametric and parametric approaches are covered, along with semi-parametric models like the Cox model, widely used in biostatistics, medical research, and reliability engineering.

Course Content:

Module I: Foundations of Statistical Quality Control

Juran and Deming's philosophies, Six Sigma methodology, and the DMAIC process, Shewhart control charts for variables ($\bar{X}$-R, $\bar{X}$-S charts) and attributes (p, c, u charts), Process capability analysis, measurement system analysis via Gauge R&R studies.

Module II: Advanced Process Monitoring Techniques

CUSUM and EWMA charts, Multivariate process monitoring (Hotelling's T^2 and MEWMA charts) , control charts for short production runs, nonparametric methods, and autocorrelated process data,

Module III: Acceptance Sampling and Reliability

Acceptance Sampling Plans: MIL-STD-105E (Attributes Sampling), MIL-STD-414 (Variables Sampling), Dodge-Romig Acceptance Sampling Systems, Reliability Engineering: Failure Distributions (Weibull, Exponential), Accelerated Life Testing, System Reliability Models, Continuous Sampling Plans.

Module IV: Advanced Quality Management Tools and Recent Trends

Taguchi Loss Function and Robust Design, Quality Function Deployment (QFD), Kaizen Philosophy and Continuous Improvement, Benchmarking Process and Applications, Lean Management and 5S Principles

List of practical to be performed using R/R-studio/Python:

1. Construct and interpret $\bar{X}$-R and $\bar{X}$-S control charts for variable quality characteristics in a production process.
2. Develop p-chart and u-chart using attribute data to monitor defect proportions and defect counts.
3. Perform Process Capability Analysis (Cp, Cpk) to assess how well a process meets specification limits.
4. Conduct a Gauge R&R study to evaluate measurement system variation and operator consistency.
5. Apply CUSUM and EWMA control charts to detect small shifts in process mean over time.
6. Design an Attribute Sampling Plan using MIL-STD-105E and draw its Operating Characteristic (OC) curve.
7. Apply Taguchi Loss Function to evaluate costs associated with deviation from the target value.
8. Create a Quality Function Deployment (QFD) matrix to translate customer needs into design specifications.

Evaluation:

<table>
<tr><td>Mode of Evaluation</td><td colspan="4">Hybrid</td></tr>
<tr><td rowspan="3">Weightage</td><td colspan="2">Comprehensive and Continuous Assessment</td><td colspan="2">End Semester Examination</td></tr>
<tr><td>Theory</td><td>Practical</td><td>Theory</td><td>Practical</td></tr>
<tr><td>25%</td><td>25%</td><td>25%</td><td>25%</td></tr>
</table>

Text Books:

T1. Montgomery, D. C. (2019). Introduction to statistical quality control (8th ed.). Wiley.

T2. Schilling, E. G., & Neubauer, D. V. (2009). Acceptance sampling in quality control (3rd ed.). CRC Press.

T3. Besterfield, D. H. (2018). Quality control (9th ed.). Pearson.

Reference Books:

R1. MIL-STD-1916, DoD Preferred Methods for Acceptance of Product

R2. Pyzdek, T. (2003), The Six Sigma Handbook, McGraw-Hill

Course Title	**Statistical Genetics**
Course Code	**SDS512**
Credit	**4**
Contact Hours (L-T-P)	**3-1-0**
Course Type	**Theory**
Pre requisites	**Design of Experiments, Statistical Inference**

Course Objectives:
The objectives of this course are as follows:

- To make students proficient in understanding and applying foundational genetic principles, including Mendel's Laws, meiosis, and genetic architecture.
- To enable students to analyze genetic data through regression models and assess parametric versus nonparametric approaches in quantitative genetics.
- To develop skills in linkage mapping, gene mapping, and marker-based analysis for practical applications in breeding and disease research.
- To analyze complex genetic structures and estimate genetic parameters in plant and animal populations, including pedigree-based linkage and identity-by-descent estimation.
- To enable students to apply advanced genomic techniques, such as QTL mapping, GWAS, and genomic selection, to real-world genetic research and problem-solving.

Course Outcomes:
On completion of this course, the students will be able to:

CO1. **Recall** foundational genetic principles including Mendel's laws, chromosomal behavior, and basic inheritance patterns to establish a basis for quantitative genetic analysis.
CO2. **Explain** the concepts of linkage, mapping, heritability, and genetic architecture, and differentiate between parametric and nonparametric models used in genetic inference.
CO3. **Apply** statistical models and marker-based methods to perform linkage analysis, map genes, and estimate genetic parameters using real or simulated genetic data.
CO4. **Analyze** complex genetic structures and pedigree-based data, incorporating strategies for handling distorted markers and evaluating identity-by-descent in populations.
CO5. **Evaluate** the effectiveness of various QTL mapping approaches, such as interval mapping, EM algorithms, and Bayesian models, in detecting genetic loci associated with traits.
CO6. **Create** predictive models and design simulation-based experiments for genetic model validation, genomic selection, and systems biology applications in diverse biological systems.

Course Description:
This course covers advanced genetic principles and statistical techniques used in genetic research. Students will explore Mendelian genetics, linkage analysis, and gene mapping, with a focus on quantitative trait loci (QTL) mapping. Topics include regression in quantitative genetics, parametric and nonparametric models, heritability, linkage estimation, marker testing, and QTL detection using linear models, Bayesian methods, and composite interval mapping. The course also addresses advanced techniques for analyzing complex genetic structures, including recombinant inbred lines, pedigree analysis, and simulations for model validation.

By the end, students will gain practical skills in genetic data analysis and its applications in genomics and systems biology.

Course Content:

Module I: Principles of Genetic Inference and Quantitative Traits

Foundations of Genetic Principles, Genes and Chromosomes, Mendel's Laws and Meiosis, Linkage and Mapping Concepts, Basic Regression in Quantitative Genetics, Parametric vs Nonparametric Models, Heritability and Genetic Architecture, Bias-Variance in Genetic Prediction, Applications in Genetic Risk Prediction.

Module II: Linkage Mapping and Marker-Based Genetic Analysis

Linkage Analysis and Gene Mapping, Mendelian Segregation Patterns, Marker Testing and Segregation Distortion, Two- and Three-Point Linkage, Locus Ordering via Likelihood, Informative Marker Linkage Estimation, Practical Use of Linkage Maps in Breeding and Disease Studies.

Module III: Complex Genetic Systems and Population-Based Inference

Estimation in Complex Genetic Structures, RILs by Selfing and Sibling Mating, Modelling Misclassified Marker Data, Viability Models, Simulation for Model Validation, Linkage in Pedigrees, Identity-By-Descent Estimation, Genetic Analysis in Plant and Animal Populations.

Module IV: Quantitative Trait Loci Mapping and Genomic Applications

QTL Mapping and Regression Models, Genetic Marker Analysis, Interval Mapping with Likelihood Estimation, Mixture and Bayesian Models, EM Algorithms, Thresholding and Cross-Validation, Composite and Multiple Interval Mapping, Applications in Genomic Selection, GWAS, and Systems Biology.

Evaluation:

Mode of Evaluation	**Theory**	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books:

T1. Wu, R., Casella, G., & Ma, C. X. (2007). Statistical genetics of quantitative traits: linkage, maps, and QTL. New York, NY: Springer New York.

T2. Narain, P. (1990). Statistical genetics (1st ed.). Wiley.

Reference Books:

R1. Moltke, I., Balding, D. J., & Marioni, J. (2019). Handbook of statistical genomics (4th ed.). Wiley.

R2. Mills, M. C., Barban, N., & Tropf, F. C. (2020). An introduction to statistical genetic data analysis (1st ed.). The MIT Press.

Course Title	**Cryptography and Network Security**
Course Code	**MTH502**
Credit	**4**
Contact Hours (L-T-P)	**3-1-0**
Course Type	**Theory**
pre requisites	**Basic number theory**

Course Objectives:

The objectives of this course are as follows:

- To understand basics of Cryptography and Network Security.
- To be able to secure a message over insecure channel by various means.
- To learn about how to maintain the Confidentiality, Integrity and Availability of a data.
- To understand various protocols for cyber security to protect against the threats in the cyber space.

Course Outcomes:

On completion of this course, the students will be able to:

CO1. Define the basics of OSI security model and Classical Encryption Technique.

CO2. Understand and identify the application of Public Key Encryption Techniques and practices.

CO3. Demonstrate the application of Data Authentication and Authorization.

CO4. Examine the basics concept of Network Security and Web Security.

CO5. Appraise the recent threats and attacks against the technical world and design some effective prevention scheme.

CO6. Apply the concept of Elliptic curve in various cryptographic algorithms.

Course Description:

Effective network communication is an integral part of technical life. Cyber Security and Cryptography is a process of securing the data communication, all the algorithms, messages etc. In this course you will learn the inner workings of cryptographic systems and how to correctly use them in real-world applications. The course begins with a detailed discussion of how two parties who have a shared secret key can communicate securely when a powerful adversary eavesdrops and tampers with traffic. We will examine many deployed protocols and analyze mistakes in existing systems. The second half of the course discusses public-key techniques that let two parties generate a shared secret key. Throughout the course participants will be exposed to many exciting open problems in the field and work on fun (optional) programming projects. In the course cybersecurity we will cover more advanced security tasks such as zero-day vulnerability, privacy mechanisms, and other forms of encryption.

Course Content:

Module I

Analyzing Unconditional Security: Plaintext Distribution, Key Distribution, Ciphertext Distribution, Attacker's Probabilities, Condition for Perfect Secrecy, Mechanism of Twisted Shift Cipher, Shannon's Theorem, One Time Pad (Verman's Cipher), and Limitations of Perfect Secrecy.

Quantification of Information: Entropy, Entropy and Coding, Measurement of the Redundancy in a Language, Conditional Entropy, Joint Entropy, Entropy and Encryption, Unicity Distance.

Classical Cryptosystems: Ciphers, Symmetric Algorithms, Asymmetric Algorithms, Encryption, Attacker's Capabilities, Kerckhoff's Principle for cipher design, Shift Cipher, Substitution Cipher, Polyalphabetic Ciphers, Vigenère Cipher, Affine Cipher, Hill Cipher, Permutation Cipher, Block Ciphers, Stream Ciphers, Product Ciphers, Affine Cipher, Idempotent Ciphers, Iterative Cipher.

Module II

Public key Cryptosystems: One Way Functions, Trapdoor One Way Function, RSA Algorithm, RSA Encryption and Decryption, Randomized Algorithms for Primality Testing using Monte-Carlo method, Finding Large Primes (using Fermat's Theorem), Fermat's Primality Test and its limitation, Strong probable-primality test, Miller-Rabin Primality Test, Miller-Rabin Algorithm (test for composites), Quadratic Residues, Legendre Symbol, Euler's Criteria, Quadratic Non Residue, Solovay Strassen Primality Test, Jacobi Symbol and its properties, Digital Signatures, Digital Certificates.

Factoring Algorithms: Pollard p-1 Factorization, Pollard Rho Algorithm, ElGamal Public Key Cryptosystem, Shank's Algorithm (also known as Baby-step Giant-step)

Key Exchange Protocols: Diffie Hellman Problem

Hash Functions: Avalanche Effect, Hash Family, Unkeyed-Hash Function, Preimage Resistant of Hash Function (one-wayness problem), Second Preimage of Hash Function, Collision Resistance of Hash Function, Random Oracle Model, Independence Property of Hash Function, RO model and Las Vegas randomized algorithm, Birthday Paradox

Module III

Elementary Concepts of Coding Theory: Basic assumptions about channels (Code length preservation, Independence of errors), Basic strategy for decoding (maximal likely-hood principle, nearest neighbour decoding strategy etc.), Hamming distance and its properties, Basic error correcting theorem, Binary symmetric channel, parity-check bit, two-dimensional parity code, Hadamard code, International Standard Book Number (ISBN)-code

Module IV

Private Key Cryptosystems: Modern techniques, algorithms like DES, AES, IDEA, RC5, Blowfish.

Module V

Elliptic Curves Theory and Applications to Factorization: Elliptic curve Diffie–Hellman (ECDH) key agreement scheme, Elliptic Curve Integrated Encryption Scheme (ECIES), Elliptic Curve Digital Signature Algorithm (ECDSA)

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Text Books:

T1. Stinson, D. R. (2002). Cryptography: Theory and practice (2nd ed.). Chapman & Hall/CRC.

T2. Forouzan, B. A. (2007). Cryptography and network security. Tata McGraw-Hill.

T3. Stallings, W. (2014). Cryptography and network security (6th ed.). Pearson Education.

T4. Mao, W. (2004). Modern cryptography: Theory and practice. Pearson Education.

Reference Books:

R1. Silverman, J. H., Pipher, J., & Hoffstein, J. (2008). An introduction to mathematical cryptography (Vol. 1). Springer New York.

R2. Joux, A. (2009). Algorithmic cryptanalysis. Chapman and Hall/CRC..

R3. Telang, S. G. (1996). Number theory. Tata McGraw-Hill.

Course Title	**Cloud Computing**
Course Code	**CSE581**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Basic knowledge of computer programming, operating systems, computer networks**

Course Objectives:

Introduce fundamental concepts of cloud computing with a focus on mathematical applications.
Explore service models (IaaS, PaaS, SaaS) and deployment models (public, private, hybrid).
Examine how cloud infrastructure supports scientific computing and big data analytics.
Provide hands-on experience with cloud platforms and tools.

Course Outcomes:

On completion of this course, the students will be able to:

- **CO1:** Understand the core concepts, architecture, and service models of cloud computing.
- **CO2:** Use cloud platforms (e.g., Google Cloud, AWS, Azure) to perform mathematical and statistical computations.
- **CO3:** Deploy and manage virtual machines and containerized applications in the cloud.
- **CO4:** Analyze, visualize, and interpret data using cloud-based tools like Google Colab and RStudio Cloud.
- **CO5:** Apply cloud-based machine learning and forecasting techniques to real-world datasets.
- **CO6:** Evaluate cloud security principles, access control, and ethical considerations in cloud environments.

Course Description:

This course introduces the fundamentals of cloud computing and its applications in scientific and data-driven domains, particularly for mathematics and statistics. Students will learn about cloud service models, virtualization, distributed computing, storage solutions, and cloud-based tools for data analysis and modeling. Emphasis is placed on hands-on experience with platforms such as Google Cloud, AWS, and Azure, using tools like Google Colab, RStudio Cloud, and cloud-based Python/R programming environments. Students will develop the ability to deploy scalable applications, perform large-scale statistical computations, and apply machine learning models using cloud services.

Course Content:

Module I: Introduction to Cloud Computing, Architecture and Virtualization, Evolution of Computing: Cluster, Grid, and Cloud, Definition and Key Characteristics of Cloud Computing, Cloud Service Models: IaaS, PaaS, SaaS, Deployment Models: Public, Private, Hybrid, Community, Advantages and Limitations of Cloud Computing, Cloud Architecture: Layers and Components, Introduction to Virtualization and Hypervisors, Containers vs. Virtual Machines, Resource Provisioning and Scalability, Load Balancing and Elasticity in Cloud Systems, Multitenancy Models and Cost Efficiency, Virtualization Technologies (Docker, KVM, Xen), Storage Solutions in Cloud: Object, Block, File, Cloud Networking Basics, Mathematical

Modeling of Resource Allocation (e.g., Linear Programming), Task Scheduling Algorithms, Case Studies: Cloud in Mathematical and Scientific Applications.

Module II: Cloud Programming and Tools:

Introduction to Python and Scientific Libraries (NumPy, SciPy), Using Jupyter and Google Colab in the Cloud, Data Visualization (Matplotlib, Seaborn, Plotly), APIs and REST in Cloud Applications, Introduction to Serverless Computing (e.g., AWS Lambda, Google Functions), Hands-on with Cloud Storage (e.g., AWS S3, Google Drive APIs), Cloud IDEs and GitHub Collaboration.

Cloud-Based Data Science and Machine Learning:

Big Data Concepts and Hadoop Ecosystem, Introduction to Apache Spark for Distributed Processing, Machine Learning in the Cloud: Overview (SageMaker, Vertex AI), Mathematical Concepts: Regression, PCA, Clustering, Training ML Models in Google Colab, Cloud Pipelines for Data Processing, Real-time Stream Analytics (e.g., Google Dataflow)

Module III:

Security, Ethics, and Research Applications

Cloud Security Fundamentals and Threat Models, Role-Based Access Control and Mathematical Models, Cryptography in Cloud (Hashing, Encryption, PKI), Introduction to Blockchain in Decentralized Cloud.

Practical/Lab to be performed on a computer using AWS Platform:

1. Introduction to cloud computing; hands-on with AWS, Google Cloud, or Azure to explore cloud dashboards and resources.
2. Use Google Colab for performing matrix operations, solving systems of equations using NumPy, and plotting mathematical functions using Matplotlib.
3. Perform descriptive statistics, data visualization, and correlation analysis using RStudio Cloud or R in Google Colab.
4. Launch and configure a virtual machine on AWS EC2 or GCP; install necessary packages for scientific computation and run sample mathematical scripts.
5. Upload, manage, and access datasets using AWS S3 or Google Cloud Storage; integrate storage with Python/R for statistical data processing.
6. Create visualizations of mathematical and statistical data using Seaborn, Plotly, or Matplotlib in cloud-based notebooks.
7. Build and evaluate linear regression models using scikit-learn or R; apply models to real-world datasets within Google Colab. Analyze and forecast time-dependent data using Python (statsmodels) or R; implement moving averages and trend visualization.
8. Use Apache Spark in Colab or Databricks to process large datasets; perform statistical summaries and explore distributed computing basics.
9. Create and deploy a serverless function on AWS Lambda or Google Cloud Functions to compute mean, median, or variance from input datasets via API.
10. Understand cloud security fundamentals, create IAM roles and policies in AWS or GCP to manage access control for cloud resources.
11. Design and implement a mini-project using cloud platforms such as a statistical dashboard, optimization solver, or simulation model integrating cloud services.

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books

T1. Buyya, R., Broberg, J., & Goscinski, A. (2011). Cloud computing: Principles and paradigms. Wiley.
T2. Erl, T. (2013). Cloud computing: Concepts, technology & architecture. Prentice Hall.
T3. Buyya, R., Vecchiola, C., & Selvi, S. T. (2013). Mastering cloud computing. McGraw Hill Education.
T4. Bahga, A., & Madisetti, V. (2014). Cloud computing: A hands-on approach. Universities Press.
T5. Lakshmanan, V. (2017). Data science on the Google Cloud Platform. O'Reilly Media.

Reference Books

R1. Hwang, K., Dongarra, J., & Fox, G. C. (2012). Distributed and cloud computing: From parallel processing to the Internet of Things. Morgan Kaufmann.
R2. Sosinsky, B. (2011). Cloud computing Bible. Wiley.
R3. Foster, I., & Gannon, D. (2017). Cloud computing for science and engineering. MIT Press.
R4. Scavetta, R. J., & Angelov, B. (2021). Python and R for the modern data scientist. Manning Publications.
R5. Wittig, M., & Wittig, A. (2018). Amazon Web Services in Action (2nd ed.). Manning Publications.

Course Title	**Natural Language Processing**
Course Code	**SDS513**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Basic knowledge of programming, data structures, probability and statistics, and linear algebra**

Course Objectives:
The objectives of this course are as follows:

- To make students familiar with foundational concepts and techniques in Natural Language Processing, including text representation, classification, and evaluation metrics.
- To enable learners to apply both classical machine learning and deep learning methods to solve real-world NLP problems like spam detection and sentiment analysis.
- To develop a strong understanding of sequence modeling techniques and their applications in tasks such as part-of-speech tagging and named entity recognition.
- To analyze the strengths and limitations of various NLP models and feature engineering techniques across different linguistic tasks and domains.
- To enable students to design and implement complete NLP pipelines, integrating preprocessing, model training, and performance evaluation for diverse applications.

Course Outcomes:
On completion of this course, the students will be able to:

CO1: Recall fundamental concepts and terminology in Natural Language Processing, including core models, learning paradigms, and evaluation metrics.
CO2: Explain the principles behind classical and deep learning approaches for text classification, sequence modeling, and information extraction.
CO3: Apply machine learning and deep learning algorithms to solve NLP tasks such as sentiment analysis, spam detection, and named entity recognition.
CO4: Analyze textual data using various feature extraction methods, model architectures, and evaluation techniques to determine their effectiveness.
CO5: Evaluate the performance of NLP models using appropriate metrics like precision, recall, F1-score, and statistical significance tests.
CO6: Create end-to-end NLP applications by integrating preprocessing, modeling, and evaluation components for real-world language understanding tasks.

Course Description:
This course offers a comprehensive introduction to Natural Language Processing (NLP), spanning foundational methods to advanced deep learning and machine reading. Students will explore core techniques such as text classification, sequence modeling, and information extraction, using models from Naive Bayes to neural networks. Topics include sentiment analysis, named entity recognition, and question answering, with applications in spam detection, social media, and finance. The course blends theoretical foundations with practical implementation, emphasizing evaluation metrics, optimization techniques, and real-world problem solving.

Course Content:

Module I: Foundations of Natural Language Processing and Text Classification

Introduction to Natural Language Processing; Core Concepts: Learning, Search, and Representations; Bag-of-Words and Vector Space Models; Naive Bayes and Smoothing; Discriminative Learning with Perceptron and Logistic Regression; Regularization and Gradient-Based Optimization; Model Evaluation Metrics: Precision, Recall, F1-Score.

Module II: Deep Learning for NLP and Linguistic Applications

Feedforward Neural Networks and Activation Functions; Dropout and Network Design Principles; Backpropagation and Optimization Techniques; Convolutional Networks in Text Classification; Applications in Sentiment Analysis and Word Sense Disambiguation.

Module III: Sequence Modeling and Unsupervised Learning in NLP

N-gram Language Models and Smoothing; Recurrent Networks (RNNs, GRUs) and Backpropagation Through Time; Sequence Labeling with HMMs, CRFs; Named Entity Recognition and POS Tagging.

Module IV: Information Extraction and Machine Reading

Entity Recognition and Linking with Learning-to-Rank; Collective Inference for Disambiguation; Supervised Relation Extraction; Knowledge Base Population and Open IE; Event Detection; Managing Hedges and Negations in Text; Machine Reading and Formal Semantics.

List of Experiments using Python

1. **Spam Detection using Naive Bayes and Logistic Regression:** Implement text preprocessing and feature extraction techniques to build classifiers that distinguish spam from legitimate messages using Naive Bayes and Logistic Regression algorithms.
2. **Sentiment Analysis using Feedforward Neural Networks:** Build and train a feedforward neural network to classify text data based on sentiment, utilizing word embeddings for input representation.
3. **Text Classification with Convolutional Neural Networks (CNNs):** Develop CNN models to perform text classification tasks by applying convolutional filters over embedded word sequences to capture semantic features.
4. **Named Entity Recognition (NER) with Bi-LSTM:** Implement a Bi-directional LSTM combined with Conditional Random Fields to identify and classify named entities in text sequences.
5. **Relation Extraction for Knowledge Base Population:** Extract semantic relationships between entities from text using dependency parsing and machine learning techniques to populate structured knowledge bases.
6. **Fake News Detection using NLP and Deep Learning:** Build and evaluate deep learning models, such as LSTM or transformer-based classifiers, to detect and classify fake news articles using NLP preprocessing techniques.

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books:

T1. Jurafsky, D., & Martin, J. H. (2009). Speech and language processing: An introduction to natural language processing, computational linguistics, and speech recognition (2nd ed.). Pearson.

T2. Manning, C. D., & Schütze, H. (1999). Foundations of statistical natural language processing (1st ed.). MIT Press.

Reference Books

R1. Goldberg, Y. (2017). Neural network methods for natural language processing (1st ed.). Morgan & Claypool Publishers.

R2. Goyal, P., Pandey, S., & Jain, K. (2020). Deep learning for natural language processing (1st ed.). Springer.

Course Title	**Reliability Theory**
Course Code	**SDS514**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Probability theory and distributions, programing skill**

Course Objectives:

To develop the ability to model and analyze the reliability of systems and components, understand the behavior of life distributions, and apply appropriate statistical and probabilistic tools for evaluating and improving system performance and maintenance.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: Define fundamental concepts of survival analysis such as censoring, truncation, survival function, and hazard function.

CO2: Explain methods for estimating survival curves using life table and Kaplan-Meier techniques.

CO3: Apply non-parametric tests like the log-rank and Wilcoxon test to compare survival distributions between groups.

CO4: Analyze parametric survival models including exponential, Weibull, and log-normal to estimate and interpret parameters.

CO5: Evaluate the assumptions of Cox proportional hazards regression models using graphical and statistical diagnostics.

CO6: Construct complete survival analysis solutions using real-world time-to-event data by integrating suitable statistical models.

Course Description:

This course offers an in-depth study of reliability theory, focusing on coherent system structures, life distributions, and stochastic models. Topics include system reliability, hazard functions, ageing properties, shock models, and maintenance strategies. The course combines theoretical foundations with practical approaches to reliability estimation and system modeling.

Course Content:

Module I:

Introduction to Reliability and its needs; Structural properties of coherent system: components and systems, coherent structures, representation of coherent systems in terms of paths and cuts, relevant & irrelevant structure; Modules of coherent systems; Reliability of a coherent systems; Reliability importance of components; Bounds on System Reliability.

Module II:

Concept of distribution function, hazard function, Reliability function, MTTF, Bathtub failure rate; loss of memory property of Exponential distribution - parametric families of some common life distributions – Exponential, Weibull and Gamma and its characterization - Reliability estimation of parameters in these models.

Module III:

Notions of Ageing; Classes of life distributions and their duals - preservation of life distribution classes for reliability operation - Formation of coherent systems, convolutions and mixtures.

Module IV:

Univariate stock models and life distributions arising out of them: cumulative damage model, shock models leading to univariate IFR, Successive shock model; bivariate shock models; common bivariate exponential distributions due to shock and their properties. Maintenance and replacement policies; availability of reparable systems; modelling of a repairable system by a non-homogeneous Poisson process.

List of Experiment:

1. Simulation of Coherent Systems Using Path and Cut Sets
2. Reliability Evaluation of Coherent Structures with Redundant Components
3. Analysis of Component Importance in System Reliability
4. Computation of System Reliability Bounds Using Structural Properties
5. Simulation of Exponential Distribution and Verification of Memoryless Property
6. Estimation of Reliability Functions and MTTF for Parametric Life Distributions
7. Comparison of Exponential, Weibull, and Gamma Life Models Using Real or Simulated Data
8. Analysis of Ageing Properties and Classification of Life Distributions
9. Simulation of Shock Models and Univariate/Bivariate Lifetime Distributions
10. Modelling of Repairable Systems Using Non-Homogeneous Poisson Processes (NHPP)

Evaluation:

Mode of Evaluation	Hybrid			
Weightage	Comprehensive and Continuous Assessment		End Semester Examination	
	Theory	Practical	Theory	Practical
	25%	25%	25%	25%

Text Books:

T1. Barlow, R.E. and Proschan F. (1985) Statistical Theory of Reliability and Life Testing; Rinehart and Winston.

T2. Lawless, J.F. (2003): Statistical Models and Methods of Life Time Data; John Wiley.

Reference Books:

R1. Bain L.J. and Max Engelhardt (1991): Statistical Analysis of Reliability and Life Testing Models; Marcel Dekker.

R2. Zacks, S (1992): Introduction to Reliability Analysis, Springer Verlag.

R3. Marshall, A.W. and Olkin I (2007): Life Distributions, Springer

Course Title	**Clinical Trials and Biostatistics**
Course Code	**SDS515**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Survival Analysis, programming skill**

Course Objectives:

To equip students with a solid understanding of statistical and analytical methods in clinical research and epidemiology, enabling them to design experiments, analyze data critically, and interpret outcomes accurately in biomedical and public health contexts.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: Understand the principles and methods of biological assays and dose-response analysis.
CO2: Explain the phases of clinical trials and apply appropriate statistical designs.
CO3: Analyze randomization techniques and blinding methods in clinical research.
CO4: Evaluate diagnostic tests using ROC curve analysis and interpret AUC and KLD concepts.
CO5: Apply epidemiological study designs such as cohort and case-control studies in research.
CO6: Identify different types of bias in clinical and epidemiological studies.

Course Description:

This course provides a comprehensive overview of biological assays, clinical trial designs, ROC curve analysis, and epidemiological methods. Students will explore statistical methods used in biomedical research, including dose-response relationships, randomization techniques, and measures of disease frequency. The course integrates theory with practical applications in pharmacokinetics, clinical trials, diagnostic testing, and public health studies.

Course Content:

Module -I

Introduction to biological assays, parallel line assay, slope ratio assay, and quantile response assay. Study of Feller's theorem, understanding dose-response relationships, including qualitative and quantitative responses, estimation of the median effective dose. Introduction to pharmacokinetic-pharmacodynamic (PK-PD) analysis.

Module -II

Introduction to clinical trials and their phases. Study of statistical designs in fixed sample trials, including simple randomized design, stratified randomized design, and crossover design. Overview of sequential designs, covering open and closed sequential designs. Discussion on randomization methods such as dynamic randomization and permuted block randomization. Understanding different types of blinding: single-blind, double-blind, and triple-blind studies.

Module -III
Estimation of the binomial model and calculation of the area under the curve (AUC) with its applications. Study of the properties of the ROC curve. Introduction to Kullback–Leibler Divergence (KLD), including its definition and the functional relationship between KLD and the slope of the ROC curve. Derivation of KLD expressions for the bi-normal ROC model.

Module -IV
Study of measures of disease frequency, including incidence, prevalence, and relative risk. Overview of epidemiological study designs, focusing on cohort study design and its analysis, and case-control study design and its analysis. Introduction to the concept of bias, including information bias and selection bias.

List of experiments (to be executed using R-Programming/Python):

1. Simulation of dose-response data and estimation of the median effective dose (ED50) using logistic or probit models.
2. Execution of parallel line assay and slope ratio assay for analysing biological assay data.
3. Analysis of clinical trial data using simple, stratified, and permuted block randomization methods.
4. Design and statistical analysis of a 2×2 crossover trial to assess treatment effects.
5. Implementation of open and closed sequential testing procedures for binary outcome clinical trials.
6. Generation and interpretation of ROC curves; estimation of area under the curve (AUC) to evaluate diagnostic performance.
7. Calculation of Kullback–Leibler Divergence (KLD) and exploration of its relationship with the slope of the ROC curve.
8. Simulation and analysis of case-control study data for the estimation of odds ratio and confidence interval.
9. Simulation of cohort study data and estimation of incidence, relative risk, and attributable risk.
10. Application of bootstrap methods to estimate bias, standard error, and confidence intervals for treatment effects in clinical data.

Evaluation:

Mode of Evaluation	**Hybrid**			
Weightage	Comprehensive and Continuous Assessment		End Semester Examination	
	Theory	Practical	Theory	Practical
	25%	25%	25%	25%

Text Books

T1. Elisa T.Lee & John Wenyu Wang (2003): Statistical methods for Survival Data analysis, 3rd Edition, John Wiley

T2. Jerrold H. Zar (1999): Biostatistical Analysis, 4th edition, Pearson

T3. Armitage, P, Berry G and Mathews J.N.S (2002): Statistical Methods in Medical

Reference Books

R1. Alan Agresti (2002): Categorical Data analysis, 2/e, John Wiley

R2. Sylvia Wasserthial and Smoller, (2004): Biostatistics and Epidemiology – A Primer for Health and Biomedical professionals, 3rd Edition, Springer

R3. Rastogi, V.B. (2006): Fundamentals of Biostatistics, ANE Books, India

Course Title	**Demography**
Course Code	**SDS516**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Elementary statistics and probability, programming skill**

Course Objectives:

This course aims to provide students with a comprehensive understanding of demographic methods and statistical techniques used in population studies. It focuses on the construction and interpretation of life tables, fertility and mortality measures, and population projections. Students will learn to analyze population structures, dynamics, and trends using both complete and incomplete data. The course prepares students for applying demographic analysis in research, planning, and policy-making.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: Identify the sources of demographic statistics and basic demographic measures.
CO2: Construct life tables and calculate mortality-related measures.
CO3: Analyze fertility patterns, differential fertility, and stable population models.
CO4: Estimate population changes using component methods based on mortality, fertility, and migration.
CO5: Apply direct and indirect standardization techniques for mortality and morbidity data.
CO6: Interpret demographic measures from incomplete data and assess population ageing.

Course Description:

The course covers fundamental and measures of demographic statistics, including ratios, rates, and population pyramids. It delves into life table construction, mortality and morbidity measures, fertility analysis, and stable population theory. Students will also study methods for population estimation and projection, addressing aspects like ageing and migration. Practical emphasis is placed on interpreting demographic data and applying standardization techniques.

Course Content:

Module I:

Sources of demographic Statistics, Basic demographic measures: Ratios, Proportions and percentages, Population Pyramids, Sex ratio Crude rates, Labor force participation rates, Density of population, Probability of dying.

Module II:

Construction of a life table, Graphs of lx, qx, dx, Functions Lx, Tx, and Ex. Abridged life tables Mortality: Rates and Ratios, Infant mortality, Maternal mortality, expected number of deaths, Direct and Indirect Standardization, Compound analysis, Morbidity.

Module III:

Measures of Fertility, reproductively formulae, Rates of natural increase, Fertility Schedules, Differential fertility, Stable Populations, Calculation of the age distribution of a stable population, Model Stable Populations.

Module IV:
Population estimates, Component method, Mortality basis for projections, Fertility basis for projections, Migration basis for projections. Ageing of the population, Estimation of demographic measures from incomplete data.

List of experiments (to be executed using MS-Excel / R-programing)

1. Simulation and visualization of population pyramids and calculation of demographic ratios, proportions, percentages, sex ratio, and population density.
2. Calculation and graphical representation of crude birth rate, crude death rate, and labor force participation rate using census-like datasets.
3. Construction of a complete life table from age-specific mortality rates and plotting the life table functions
4. Construction of an abridged life table using grouped age intervals and calculation of life expectancy at birth
5. Calculation of infant mortality rate, maternal mortality rate, and expected number of deaths using R
6. Estimation of standardized mortality rates using both direct and indirect standardization techniques
7. Analysis of fertility measures including crude birth rate, general fertility rate, age-specific fertility rates, and total fertility rate using sample data
8. Computation of fertility schedules and analysis of differential fertility across different groups
9. Calculation and graphical presentation of the age distribution of a stable population and exploration of model stable population structures
10. Implementation of the component method for population projection considering fertility, mortality, and migration; and estimation of demographic measures from incomplete or partial data

Evaluation:

Mode of Evaluation	**Hybrid**			
Weightage	Comprehensive and Continuous Assessment		End Semester Examination	
	Theory	Practical	Theory	Practical
	25%	25%	25%	25%

Text Books

T1. Pollard, A. H. Yusuf, F. and Pollard, G.N. (1990). Demographic Techniques, Pergamon Press, Chapters 1-8, 12.

T2. Goon A.M., Gupta M.K., Das Gupta.B. (1999): Fundamentals of Statistics, Vol.II, World Press, Calcutta.

Reference Books

R1. Keyfitz, N. (1977) Applied Mathematical Demography A Willey-Intercedence Publication.

Course Title	**Big Data Analytics**
Course Code	**CSE582**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Basic knowledge of programming (preferably Python), Data Structures, Database Management Systems, Probability and Statistics**

Course Objectives:

The objective of this course is to provide students with a comprehensive understanding of big data analytics concepts, tools, and techniques. By the end of the course, students will be equipped to analyze and interpret large datasets to drive decision-making in various domains.

Course Outcomes:

On completion of this course, the students will be able to:

CO1: Identify Big Data and its Business Implications
CO2: List the components of Hadoop and Hadoop Eco-System
CO3: Outline and Process Data on Distributed File System
CO4: Plan Job Execution in Hadoop Environment
CO5: Develop Big Data Solutions using Hadoop Eco System
CO6: Illustrate Infosphere Big Insights Big Data Recommendations

Course Description:

This course provides an in-depth exploration of big data analytics, focusing on the concepts, technologies, and methodologies used to analyze vast amounts of data to uncover valuable insights. As organizations increasingly rely on data to inform their decisions, this course equips students with the skills necessary to navigate the complexities of big data. The course begins by defining big data and its core characteristics—volume, velocity, variety, veracity, and value. Students will learn about the significance of big data analytics in various sectors and how it transforms data into actionable insights. Key technologies in big data analytics, including Hadoop, Apache Spark, and NoSQL databases, will be thoroughly examined. Students will explore the architecture of these technologies and their practical applications in processing and analyzing large datasets. Hands-on experience will be a crucial component of the course, where students will engage in data preparation, cleaning, and transformation techniques essential for effective analysis. The course will also cover statistical methods and machine learning algorithms applicable to big data, such as regression analysis, classification, clustering, and recommendation systems. Data visualization techniques will be introduced to help students effectively communicate their findings. The course will emphasize the importance of visual storytelling in making complex data understandable and actionable. Ethical considerations related to big data analytics, including privacy, security, and data governance, will be discussed to prepare students for the responsibilities that come with handling sensitive information. Real-world case studies will provide students with practical insights into how big data analytics is applied across various industries, including healthcare, finance, marketing, and social media. By analyzing these cases, students will learn best practices and the challenges faced when implementing big data solutions. Through lectures, hands-on labs, discussions, and projects, students will develop the skills to design and implement big data analytics projects. By the end of the course, students will be well-prepared to leverage big data analytics to drive informed decision-making in their professional careers.

Course Content:

Module I: Introduction to big data

Introduction to Big Data Platform, Challenges of Conventional Systems, Intelligent data analysis, Nature of Data, Analytic Processes and Tools, Analysis vs Reporting

Module II: Mining data streams

Introduction to Streams Concepts, Stream Data Model and Architecture, Stream Computing, Sampling Data in a Stream, Filtering Streams, Counting Distinct Elements in a Stream, Estimating Moments, Counting Oneness in a Window, Decaying Window, Real-time Analytics Platform (RTAP) Applications, Case Studies, Real-Time Sentiment Analysis, Stock Market Predictions

Module III: Hadoop

History of Hadoop, the Hadoop Distributed File System, Components of Hadoop Analysing the Data with Hadoop, Scaling Out, Hadoop Streaming, Design of HDFS-Java interfaces to HDFS Basics, Developing a Map Reduce Application, How Map Reduce Works, Anatomy of a Map Reduce Job run-Failures, Job Scheduling, Shuffle and Sort, Task execution - Map Reduce Types and Formats, Map Reduce Features- Hadoop environment

Module IV: Frameworks

Applications on Big Data Using Pig and Hive, Data processing operators in Pig, Hive services, Hive QL, Querying Data in Hive - fundamentals of HBase and ZooKeeper, IBM InfoSphere Big Insights and Streams, Predictive Analytics, Simple linear regression, multiple linear regressions, Interpretation of regression coefficients, Visualizations, Visual data analysis techniques, interaction techniques, Systems and applications

List of experiments to be conducted in Practical class:

1. Compare performance of relational databases and big data systems on large datasets.
2. Load and analyze a large dataset using Python libraries and visualization techniques.
3. Set up data stream ingestion and apply sampling/filtering in real-time.
4. Approximate frequency counts of data stream elements using Count-Min Sketch.
5. Install Hadoop and run a basic MapReduce word count job.
6. Write a MapReduce job to analyze web server log files for hit counts.
7. Create Hive tables, load datasets, and perform SQL-like queries.
8. Perform linear/multiple regression, interpret results, and generate visualizations.

Evaluation:

Mode of Evaluation	Hybrid			
Weightage	Comprehensive and Continuous Assessment		End Semester Examination	
	Theory	Practical	Theory	Practical
	25%	25%	25%	25%

Books Recommended:

Text Books

T1. Big Data Analytics (2nd ed.). (2019). Wiley India.

T2. Big Data Fundamentals. (2015). Prentice Hall.

Reference Books

R1. White, T. (2015). Hadoop: The definitive guide (4th ed.). O'Reilly Media.

R2. Leskovec, J., Rajaraman, A., & Ullman, J. D. (2020). Mining of massive datasets (3rd ed.). Cambridge University Press.

R3. Han, J., Kamber, M., & Pei, J. (2012). Data mining: Concepts and. Techniques, Waltham: Morgan Kaufmann Publishers, 2012-13.

R4. Chambers, B., & Zaharia, M. (2018). Spark: The definitive guide: Big data processing made simple. " O'Reilly Media, Inc.".

Course Title	Cyber Security for Data Science
Course Code	CSE583
Credit	4
Contact Hours (L-T-P)	3-0-2
Course Type	Theory
Pre requisites	Basic knowledge of computer fundamentals, programming, operating systems, and computer networks

Course Objective

The objective of this course is to provide students with a comprehensive understanding of cybersecurity threats, vulnerability analysis, and protection tools used across various layers of networks and web applications. The course aims to:

1. Introduce fundamental concepts of system and network vulnerability scanning, including tools and techniques such as Nmap, sniffers, and injection utilities.
2. Familiarize students with network protection mechanisms, including firewalls, intrusion detection/prevention systems, VPNs, and malware defense tools.
3. Develop practical skills in using web security tools and password auditing utilities to identify and mitigate common web-based and authentication vulnerabilities.
4. Enable learners to understand and analyze the landscape of cybercrime, digital forensics, and relevant legal frameworks, particularly in the Indian context.
5. Equip students with the knowledge to conduct cybercrime investigations involving various attack vectors, such as malware, DDoS, SQL injection, and techniques like penetration testing and steganography.

Course Outcomes:

On completion of this course, the students will be able to

CO1. **Understanding** Cyber Security Fundamentals, the concepts of system and network vulnerability scanning and demonstrate the use of common sniffing and injection tools.

CO2. **Analyze** network protection mechanisms such as firewalls, VPNs, NAT, and intrusion detection systems (IDS/IPS) to secure a network infrastructure. Security Architecture and Design

CO3. **Evaluate** web security vulnerabilities and utilize appropriate tools to detect and mitigate web-based threats and password attacks.

CO4. **Explain** various types of cybercrimes, critical cyber threats, and legal frameworks including the Indian IT Act 2000.

CO5. **Apply** investigation techniques and tools for cybercrime scenarios, including password cracking, malware analysis, digital forensics, and penetration testing.

Course Content:

Module-I

Systems Vulnerability Scanning: Introduction to Vulnerability Scanning, Types of Vulnerabilities, Vulnerability vs. threat vs. risk, Open Port / Service Identification, Banner / Version Check, Traffic Probe, Vulnerability Probe, Vulnerability Examples.

Networks Vulnerability Scanning: Network-based scanners, Host-based scanners, Application-level scanners, Network Reconnaissance – N map, System tools.

Network Sniffers and Injection tools: Introduction to Network Sniffing, Types of Sniffing: Active sniffing (intercepting traffic via spoofing or flooding), Passive sniffing (e.g., on a hub-based or broadcast network), Common Sniffing Tools: Tcpdump, Wireshark, Tshark, Ettercap,

Module-II

Network Protection tools: Firewall Basics, Comparison between Packet Filter and Firewall, Proxy firewalls, Protection mechanism of Firewall, Packet Characteristic to Filter, Stateless and Stateful Firewalls, Network Address Translation (NAT) and Port Forwarding, the basic of Virtual Private Networks (VPN), Linux Firewall, Windows Firewall, Snort - Network Intrusion Detection and Prevention System, IP Security Architecture, Antivirus and Anti-malware.

Module-III

Protection tools against web vulnerabilities: Web Application Firewalls, Vulnerability Scanners: OWASP ZAP (Zed Attack Proxy), OWASP ZAP (Zed Attack Proxy), Nikto, Burp Suite, HTTP utilities - Curl, OpenSSL.

Password Cracking and Brute-Force Tools: Introduction to Password Cracking, Types of Password Attacks, Common Password Cracking Tools: John the Ripper, Hashcat, Hydra, Ncrack. Protection Against Password Cracking.

Module-IV

Cyber Crime and Law: Cyber Crimes, Types of Cybercrime, Critical cyber threats: cyber terrorism, cyber-warfare, cyber-espionage, Hacking, Attack vectors, Cyberspace and Criminal Behavior, Clarification of Terms, Traditional Problems Associated with Computer Crime, Introduction to Incident Response, Digital Forensics, Computer Language, Network Language, Realms of the Cyber world, A Brief History of the Internet, Recognizing and Defining Computer Crime, Contemporary Crimes, Computers as Targets, Contaminants and Destruction of Data, Indian IT ACT 2000. 10

Module-V

Cyber Crime Investigation: Firewalls and Packet Filters, password Cracking, Key loggers and Spyware, Virus and Warms, Trojan and backdoors, Steganography, DOS and DDOS attack, SQL injection, Buffer Overflow, Attack on wireless Networks, digital forensics, Penetration testing, related case studies.

Evaluation:

Mode of Evaluation	Theory	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination
	50%	50%

Books Recommended:

Text Books

T1. Brooks, C. J., Grow, C., Craig, P., & Short, D. (2018). Cybersecurity essentials. Cisco Press.

T2. Heard, N. A., Adams, N. M., Rubin-Delanchy, P., & Turcotte, M. (2018). Data science for cyber-security (Security Science and Technology, Vol. 3). World Scientific Publishing Europe Ltd.

Reference Books

R1. Shema, M. (2014). Anti-hacker tool kit (Indian ed.). McGraw Hill Education.

R2. Godbole, N., & Belpure, S. *Cyber security: Understanding cyber crimes, computer forensics and legal perspectives*. Wiley.

R3. ayuk, J., Mastaler, J., & McDaniel, P. (2023). *Cybersecurity for data scientists*. Springer.

R4. Stallings, W., & Brown, L. (2018). *Computer security: Principles and practice*. Pearson.

R5. M. Bhushan, R.S. Rathore, A. Jamshed, “ Cyber Security”, BPB Publication.

Course Title	**Image Processing and Computer Vision**
Course Code	**SDS517**
Credit	**4**
Contact Hours (L-T-P)	**3-0-2**
Course Type	**Hybrid**
Pre requisites	**Machine Learning, Linear Algebra, Programming skill**

Course Objectives:
The objectives of this course are as follows:

- To make students understand the fundamentals of digital image representation, enhancement, and restoration techniques.
- To enable learners to apply computational geometry and camera models for image transformation and reconstruction.
- To develop skills in feature extraction, segmentation, classification, and statistical vision models for real-world applications.
- To analyze the performance and accuracy of image processing algorithms using appropriate evaluation metrics.
- To enable students to integrate image processing and computer vision techniques to create complete application pipelines.

Course Outcomes:
On completion of this course, the students will be able to:

CO1: Recall the fundamental concepts of digital image representation, colour spaces, image formation, and basic image processing techniques.
CO2: Explain various image enhancement, restoration, transformation, and segmentation methods along with their mathematical foundations.
CO3: Apply computational geometry concepts and camera models to perform geometric transformations and multi-view image reconstruction.
CO4: Analyze image features, descriptors, and statistical properties to extract meaningful information for classification and recognition tasks.
CO5: Evaluate the performance of image processing and computer vision algorithms using quantitative metrics and comparative analysis.
CO6: Create end-to-end computer vision applications by integrating image processing, feature extraction, and statistical modeling techniques.

Course Description:
This course introduces digital image processing and computer vision, covering image representation, enhancement, restoration, feature extraction, segmentation, and classification. Students will explore camera models, multi-view geometry, temporal tracking, and statistical vision models. Emphasis is on applying mathematical concepts to real-world problems using Python. By the end, learners will be able to analyze, evaluate, and develop applications such as object detection, recognition, tracking, and lane detection, gaining both theoretical understanding and practical skills in modern image analysis techniques.

Course Content:

Module I - Fundamentals of Digital Image Processing:

Digital images and representation, resolution and quantization, colour spaces and RGB–greyscale conversion, basics of image formation (point-spread function, convolution), camera digitization and noise; basic pixel operations, histograms and contrast enhancement, image filtering (linear, median, Gaussian), edge detection (first-order, second-order, canny), and Fourier-based frequency-domain processing.

Module II - Quantitative Analysis of Image:

Image restoration (inverse, Wiener), geometric transformations (affine, projective), morphological operations (dilation, erosion, opening/closing); feature extraction (shape, PCA), segmentation (thresholding, region growing, Canny), and classification (supervised, linear discriminants, k-means).

Module III - Computational Geometry of Image:

Image preprocessing: Per-pixel transformations, edges/corners, descriptors, dimensionality reduction.

Geometry models: pinhole camera, intrinsic/extrinsic parameters, 2D transformations, two-view geometry (essential/fundamental matrices), and multi-view reconstruction.

Module IV - Statistical Models for Computer Vision:

Vision models: shape representation (statistical/subspace), 3D shape models; identity models (subspace, probabilistic LDA); temporal models (Kalman, particle filters); visual words (bag-of-words, LDA) and applications.

List of Experiments using Python

1. Palm Line Detection: Implement image acquisition and preprocessing techniques to identify and enhance palm lines using edge detection and morphological operations.
2. Face Detection: Apply Haar cascades, HOG-based methods, or deep learning models to locate faces in images or live video streams.
3. Face Recognition: Use feature extraction (e.g., LBPH, Eigenfaces, or deep embeddings) and classification techniques to identify and verify individual faces.
4. Movement Tracking: Implement motion detection and object tracking algorithms (e.g., centroid tracking, optical flow, or Kalman filter) to track moving objects in video sequences.
5. Lane Detection: Use image processing (Canny edge detection, Hough transform) and perspective transformations to detect lane markings in road images or videos.
6. Eye Detection and Blink Counting: Detect eyes within face regions and track blinking patterns for fatigue detection applications.
7. QR Code Detection and Decoding: Detect and decode QR codes from images or live video feed.

Evaluation:

Mode of Evaluation	Theory		Practical	
Weightage	Comprehensive and Continuous Assessment	End Semester Examination	Comprehensive and Continuous Assessment	End Semester Examination
	25%	25%	25%	25%

Text Books:

T1. Gonzalez, R. C. (2009). Digital image processing. Pearson education india..

T2. Jähne, B. (2005). Digital image processing. Berlin, Heidelberg: Springer Berlin Heidelberg.

T3. Jain, A. K. (1989). Fundamentals of digital image processing. Prentice Hall of India.

Reference Books:

R1. Sonka, M., Hlavac, V., & Boyle, R. (2013). Image processing, analysis and machine vision. Springer.

R2. Clarke, K. C. (2011). Getting started with geographic information systems (5th ed.). Pearson.

R3. Lo, C. P. (2009). Concepts and techniques of geographic information systems (2nd ed.). Pearson Prentice Hall.

Course Code	Course Name	COs	PO01	PO02	PO03	PO04	PO05	PO06	PO07	PO08	PO09	PO10	PO11	PO12	PSO1	PSO2	PSO3	PSO4
MTH421	**Multivariate Calculus and Applications**	**CO1**	3.00	2.00	1.00	1.00	-	-	-	-	-	-	-	2.00	2.00	1.00	2.00	1.00
		CO2	3.00	3.00	2.00	2.00	1.00	1.00	-	-	-	1.00	-	3.00	3.00	2.00	3.00	2.00
		CO3	2.00	2.00	3.00	3.00	3.00	2.00	-	-	1.00	-	-	3.00	3.00	2.00	3.00	3.00
		CO4	3.00	3.00	2.00	2.00	1.00	-	-	-	-	-	-	2.00	2.00	1.00	2.00	2.00
		CO5	3.00	3.00	2.00	3.00	2.00	2.00	-	-	1.00	1.00	-	3.00	3.00	2.00	3.00	3.00
		CO6	2.00	2.00	3.00	3.00	3.00	2.00	-	-	2.00	1.00	1.00	3.00	3.00	2.00	3.00	3.00
			2.67	**2.50**	**2.17**	**2.33**	**2.00**	**1.75**	**-**	**-**	**1.33**	**1.00**	**1.00**	**2.67**	**2.67**	**1.67**	**2.67**	**2.33**
MTH409	**Optimization Techniques**	**CO1**	3.00	3.00	2.00	2.00	2.00	1.00	-	1.00	-	-	-	2.00	2.00	2.00	2.00	1.00
		CO2	3.00	3.00	2.00	2.00	2.00	1.00	-	1.00	1.00	-	-	2.00	2.00	2.00	2.00	2.00
		CO3	3.00	3.00	2.00	3.00	3.00	1.00	-	1.00	2.00	-	-	2.00	3.00	2.00	3.00	2.00
		CO4	3.00	3.00	2.00	3.00	3.00	1.00	-	2.00	2.00	1.00	-	2.00	3.00	2.00	3.00	2.00
		CO5	3.00	3.00	2.00	3.00	3.00	1.00	-	2.00	2.00	1.00	1.00	2.00	3.00	2.00	3.00	3.00
		CO6	3.00	3.00	3.00	3.00	3.00	2.00	1.00	2.00	3.00	2.00	2.00	3.00	3.00	3.00	3.00	3.00
			3.00	**3.00**	**2.17**	**2.67**	**2.67**	**1.17**	**1.00**	**1.50**	**2.00**	**1.33**	**1.50**	**2.17**	**2.67**	**2.17**	**2.67**	**2.17**
SDS421	**Advanced Regression Techniques**	**CO1**	3.00	3.00	2.00	3.00	2.00	1.00	-	1.00	-	-	-	2.00	3.00	2.00	3.00	-
		CO2	3.00	3.00	2.00	3.00	2.00	1.00	-	1.00	-	-	-	2.00	3.00	2.00	3.00	-
		CO3	3.00	3.00	2.00	3.00	3.00	1.00	-	1.00	-	-	-	2.00	3.00	2.00	3.00	-
		CO4	3.00	2.00	2.00	3.00	3.00	2.00	-	1.00	-	-	-	2.00	2.00	3.00	3.00	-
		CO5	3.00	2.00	2.00	3.00	3.00	2.00	2.00	1.00	2.00	1.00	1.00	3.00	3.00	3.00	3.00	2.00
		CO6	3.00	2.00	2.00	3.00	3.00	2.00	2.00	1.00	2.00	1.00	1.00	3.00	3.00	3.00	3.00	2.00
			3.00	**2.50**	**2.00**	**3.00**	**2.67**	**1.50**	**2.00**	**1.00**	**2.00**	**1.00**	**1.00**	**2.33**	**2.83**	**2.50**	**3.00**	**2.00**
CSE481	**Data Structures and Algorithm Design**	**CO1**	3.00	2.00	1.00	-	-	-	-	-	-	-	-	-	2.00	-	-	-
		CO2	3.00	3.00	2.00	-	-	-	-	-	-	-	-	-	2.00	-	2.00	-
		CO3	3.00	3.00	3.00	-	-	-	-	-	-	-	-	-	2.00	-	-	-
		CO4	3.00	3.00	3.00	-	-	-	-	-	-	-	-	-	2.00	-	2.00	-
		CO5	3.00	3.00	3.00	-	-	-	-	-	-	-	-	-	2.00	-	2.00	-
		CO6	3.00	2.80	2.40	-	-	-	-	-	-	-	-	-	2.00	-	2.00	-
			3.00	**3.00**	**2.00**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**-**	**3.00**	**-**	**2.00**	**-**

MTH501	**Matrix computation**	**CO1**	3.00	3.00	2.00	3.00	3.00	1.00	1.00	2.00	1.00	1.00	2.00	2.00	3.00	3.00	3.00	2.00
		CO2	3.00	3.00	2.00	3.00	3.00	1.00	1.00	2.00	2.00	1.00	2.00	2.00	3.00	3.00	3.00	3.00
		CO3	3.00	3.00	3.00	3.00	2.00	1.00	1.00	2.00	1.00	1.00	2.00	2.00	3.00	3.00	3.00	2.00
		CO4	3.00	3.00	3.00	3.00	3.00	1.00	1.00	2.00	2.00	1.00	2.00	2.00	3.00	3.00	3.00	2.00
		CO5	3.00	3.00	3.00	3.00	3.00	1.00	1.00	2.00	3.00	2.00	3.00	3.00	3.00	3.00	3.00	3.00
		CO6	3.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	2.00	1.00	3.00	2.00	3.00	3.00	3.00	3.00
			3.00	**3.00**	**2.50**	**3.00**	**2.67**	**1.00**	**1.00**	**2.00**	**1.83**	**1.17**	**2.33**	**2.17**	**3.00**	**3.00**	**3.00**	**2.50**
SDS452	**Data Analytics for Finance**	**CO1**	1.00	2.00	2.00	3.00	2.00	1.00	2.00	1.00	2.00	0.00	1.00	2.00	2.00	1.00	2.00	3.00
		CO2	2.00	3.00	2.00	3.00	3.00	1.00	2.00	2.00	2.00	0.00	1.00	3.00	3.00	1.00	2.00	2.00
		CO3	3.00	3.00	2.00	3.00	3.00	1.00	1.00	2.00	2.00	0.00	1.00	3.00	3.00	2.00	3.00	3.00
		CO4	2.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	3.00	1.00	2.00	3.00	3.00	2.00	2.00	2.00
		CO5	3.00	3.00	3.00	3.00	3.00	1.00	2.00	2.00	2.00	1.00	2.00	3.00	3.00	2.00	2.00	3.00
			2.20	**2.80**	**2.20**	**3.00**	**2.60**	**1.00**	**1.60**	**1.80**	**2.20**	**0.40**	**1.40**	**2.80**	**2.80**	**1.60**	**2.20**	**2.60**
MTH450	**Research Methodology**	**CO1**	2.00	2.00	1.00	2.00	2.00	1.00	2.00	1.00	2.00	1.00	1.00	1.00	2.00	3.00	2.00	2.00
		CO2	1.00	2.00	1.00	2.00	2.00	2.00	3.00	2.00	1.00	0.00	1.00	1.00	2.00	2.00	1.00	1.00
		CO3	1.00	2.00	2.00	1.00	2.00	2.00	2.00	1.00	3.00	2.00	2.00	1.00	1.00	2.00	1.00	1.00
		CO4	2.00	2.00	1.00	2.00	2.00	2.00	2.00	2.00	2.00	0.00	1.00	2.00	2.00	3.00	1.00	1.00
			1.50	**2.00**	**1.25**	**1.75**	**2.00**	**1.75**	**2.25**	**1.50**	**2.00**	**0.75**	**1.25**	**1.25**	**1.75**	**2.50**	**1.25**	**1.25**
SDS423	**Python Programming**	**CO1**	2.00	3.00	2.00	3.00	2.00	1.00	2.00	2.00	1.00	0.00	1.00	3.00	2.00	2.00	2.00	3.00
		CO2	2.00	3.00	2.00	3.00	3.00	2.00	2.00	2.00	1.00	-	-	3.00	3.00	2.00	3.00	3.00
		CO3	3.00	3.00	2.00	-	3.00	2.00	2.00	3.00	2.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO4	3.00	3.00	2.00	-	3.00	-	-	3.00	2.00	-	-	-	3.00	-	2.00	3.00
		CO5	3.00	3.00	2.00	3.00	-	2.00	-	3.00	2.00	1.00	2.00	-	3.00	2.00	2.00	3.00
		CO6	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	2.00	1.00	2.00	-	3.00	3.00	3.00	3.00
			2.67	**3.00**	**2.17**	**3.00**	**2.80**	**2.00**	**2.25**	**2.67**	**1.67**	**0.75**	**1.50**	**3.00**	**2.83**	**2.20**	**2.33**	**3.00**
SDS501	**Time Series Analysis**	**CO1**	2.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	2.00	3.00	-	3.00	3.00
		CO2	2.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	2.00	3.00	-	3.00	3.00
		CO3	3.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	3.00	3.00	-	3.00	3.00
		CO4	3.00	3.00	2.00	3.00	3.00	-	1.00	-	-	-	-	3.00	3.00	-	2.00	3.00
		CO5	3.00	3.00	2.00	3.00	3.00	1.00	2.00	2.00	-	-	1.00	3.00	3.00	1.00	2.00	3.00
		CO6	3.00	3.00	3.00	3.00	3.00	2.00	2.00	2.00	1.00	-	2.00	3.00	3.00	2.00	3.00	3.00
			2.67	**3.00**	**2.17**	**3.00**	**2.50**	**1.50**	**1.67**	**2.00**	**1.00**	**-**	**1.50**	**2.67**	**3.00**	**1.50**	**2.67**	**3.00**

SDS502	**Machine Learning and Applications**	**CO1**	2.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	1.00	1.00	2.00	3.00	3.00	1.00	2.00	3.00
		CO2	2.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	1.00	0.00	1.00	3.00	3.00	1.00	2.00	3.00
		CO3	2.00	3.00	2.00	3.00	3.00	1.00	1.00	2.00	2.00	1.00	2.00	3.00	3.00	2.00	3.00	3.00
		CO4	2.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	1.00	1.00	2.00	3.00	3.00	1.00	2.00	3.00
		CO5	2.00	3.00	2.00	3.00	3.00	1.00	1.00	2.00	2.00	1.00	2.00	3.00	3.00	2.00	2.00	3.00
		CO6	3.00	3.00	2.00	3.00	3.00	2.00	1.00	3.00	2.00	1.00	2.00	3.00	3.00	2.00	3.00	3.00
			2.17	**3.00**	**2.00**	**3.00**	**2.50**	**1.17**	**1.00**	**2.17**	**1.50**	**0.83**	**1.83**	**3.00**	**3.00**	**1.50**	**2.33**	**3.00**
SDS503	**Applied Multivariate Analysis**	**CO1**	2.00	3.00	2.00	3.00	3.00	1.00	2.00	1.00	2.00	–	1.00	2.00	3.00	1.00	2.00	3.00
		CO2	1.00	3.00	2.00	3.00	3.00	–	2.00	1.00	2.00	–	–	2.00	3.00	2.00	3.00	3.00
		CO3	2.00	3.00	2.00	3.00	3.00	1.00	2.00	2.00	2.00	–	1.00	3.00	3.00	3.00	2.00	3.00
		CO4	2.00	3.00	2.00	2.00	3.00	–	2.00	2.00	3.00	–	2.00	2.00	3.00	2.00	2.00	2.00
		CO5	3.00	3.00	2.00	3.00	3.00	2.00	2.00	2.00	2.00	1.00	2.00	3.00	3.00	2.00	2.00	3.00
		CO6	3.00	3.00	2.00	3.00	3.00	2.00	2.00	3.00	2.00	1.00	2.00	3.00	3.00	2.00	2.00	2.00
			2.17	**3.00**	**2.00**	**2.83**	**3.00**	**1.00**	**2.00**	**1.83**	**2.17**	**0.33**	**1.33**	**2.50**	**3.00**	**2.00**	**2.17**	**2.67**
SDS504	**Advanced Sampling Theory**	**CO1**	3.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	2.00	3.00	-	3.00	3.00
		CO2	3.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	2.00	3.00	-	2.00	3.00
		CO3	3.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	2.00	3.00	-	3.00	3.00
		CO4	3.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	3.00	3.00	-	3.00	3.00
		CO5	3.00	3.00	2.00	3.00	2.00	1.00	2.00	2.00	-	-	1.00	3.00	3.00	-	3.00	3.00
		CO6	3.00	3.00	2.00	3.00	3.00	-	1.00	-	-	-	-	3.00	3.00	2.00	2.00	3.00
			3.00	**3.00**	**2.00**	**3.00**	**2.17**	**1.00**	**1.50**	**2.00**	**-**	**-**	**1.00**	**2.50**	**3.00**	**2.00**	**2.67**	**3.00**
SDS505	**Data Engineering**	**CO1**	2.00	3.00	2.00	3.00	2.00	1.00	2.00	2.00	1.00	0.00	1.00	3.00	2.00	1.00	2.00	3.00
		CO2	2.00	3.00	2.00	3.00	2.00	2.00	2.00	2.00	1.00	0.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO3	3.00	3.00	3.00	3.00	3.00	1.00	2.00	2.00	1.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO4	3.00	3.00	2.00	3.00	3.00	2.00	2.00	3.00	1.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO5	3.00	3.00	2.00	3.00	3.00	2.00	2.00	2.00	1.00	0.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO6	3.00	3.00	2.00	3.00	3.00	2.00	2.00	3.00	1.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
			2.67	**3.00**	**2.17**	**3.00**	**2.67**	**1.67**	**2.00**	**2.33**	**1.00**	**0.50**	**1.00**	**3.00**	**2.83**	**1.83**	**2.00**	**3.00**

SDS506	**Deep Learning and its Applications**	**CO1**	2.00	3.00	2.00	3.00	2.00	0.00	1.00	1.00	1.00	0.00	1.00	2.00	2.00	1.00	3.00	3.00
		CO2	3.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	1.00	0.00	1.00	3.00	3.00	1.00	2.00	3.00
		CO3	3.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	1.00	1.00	2.00	3.00	3.00	2.00	2.00	2.00
		CO4	2.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	1.00	0.00	1.00	3.00	3.00	2.00	3.00	2.00
		CO5	2.00	3.00	2.00	2.00	2.00	1.00	2.00	2.00	3.00	2.00	3.00	2.00	2.00	2.00	2.00	2.00
		CO6	3.00	3.00	2.00	3.00	3.00	2.00	2.00	3.00	2.00	1.00	2.00	3.00	3.00	3.00	2.00	3.00
			2.50	**3.00**	**2.00**	**2.83**	**2.17**	**1.00**	**1.33**	**2.00**	**1.50**	**0.67**	**1.67**	**2.67**	**2.67**	**1.83**	**2.33**	**2.50**
SDS507	**Survival analysis**	**CO1**	2.00	2.00	1.00	2.00	2.00	1.00	2.00	1.00	2.00	1.00	1.00	2.00	2.00	1.00	2.00	3.00
		CO2	2.00	2.00	2.00	3.00	2.00	1.00	2.00	2.00	2.00	1.00	2.00	3.00	3.00	1.00	2.00	3.00
		CO3	2.00	3.00	2.00	3.00	3.00	1.00	2.00	2.00	2.00	1.00	2.00	3.00	3.00	1.00	2.00	2.00
		CO4	3.00	3.00	3.00	3.00	3.00	1.00	2.00	2.00	3.00	1.00	2.00	3.00	3.00	2.00	3.00	3.00
		CO5	3.00	3.00	3.00	3.00	3.00	2.00	2.00	2.00	3.00	1.00	2.00	3.00	3.00	3.00	3.00	3.00
		CO6	3.00	3.00	3.00	3.00	3.00	2.00	3.00	3.00	3.00	2.00	3.00	3.00	3.00	3.00	2.00	3.00
			2.50	**2.67**	**2.33**	**2.83**	**2.67**	**1.33**	**2.17**	**2.00**	**2.50**	**1.17**	**2.00**	**2.83**	**2.83**	**1.83**	**2.33**	**2.83**
SDS508	**Mathematical Modelling**	**CO1**	2.00	2.00	2.00	2.00	2.00	-	-	-	-	-	-	2.00	2.00	-	2.00	3.00
		CO2	3.00	3.00	3.00	3.00	2.00	-	-	-	-	2.00	2.00	2.00	3.00	-	2.00	3.00
		CO3	3.00	3.00	2.00	3.00	3.00	-	1.00	-	-	-	2.00	3.00	3.00	-	3.00	3.00
		CO4	3.00	3.00	2.00	3.00	3.00	-	-	-	-	-	2.00	3.00	3.00	-	3.00	3.00
		CO5	3.00	3.00	2.00	3.00	3.00	-	-	-	-	-	2.00	3.00	3.00	-	3.00	3.00
		CO6	3.00	3.00	3.00	3.00	3.00	1.00	1.00	1.00	1.00	2.00	3.00	3.00	3.00	2.00	3.00	3.00
			2.83	**2.83**	**2.33**	**2.83**	**2.67**	**1.00**	**1.00**	**1.00**	**1.00**	**2.00**	**2.20**	**2.67**	**2.83**	**2.00**	**2.67**	**3.00**
CSE584	**Artificial Intelligence and Applications**	**CO1**	1.00	2.00	1.00	2.00	2.00	0.00	2.00	1.00	2.00	0.00	1.00	2.00	1.00	1.00	2.00	3.00
		CO2	2.00	3.00	1.00	3.00	2.00	1.00	1.00	2.00	2.00	0.00	1.00	3.00	3.00	2.00	2.00	2.00
		CO3	2.00	3.00	1.00	3.00	2.00	1.00	1.00	2.00	2.00	0.00	1.00	3.00	3.00	2.00	3.00	2.00
		CO4	3.00	3.00	2.00	3.00	3.00	2.00	1.00	3.00	2.00	1.00	2.00	3.00	3.00	2.00	3.00	2.00
		CO5	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	2.00	3.00	3.00	2.00	3.00	2.00	2.00
			2.20	**2.80**	**1.60**	**2.80**	**2.40**	**1.40**	**1.60**	**2.20**	**2.20**	**0.60**	**1.60**	**2.80**	**2.40**	**2.00**	**2.40**	**2.20**

SDS510	**Stochastic Process**	**CO1**	2.00	2.00	2.00	2.00	2.00	-	-	-	-	-	-	2.00	2.00	-	3.00	3.00
		CO2	2.00	2.00	2.00	3.00	2.00	-	-	-	-	-	-	2.00	3.00	-	3.00	3.00
		CO3	3.00	3.00	2.00	3.00	3.00	-	-	-	-	-	1.00	3.00	3.00	-	3.00	3.00
		CO4	3.00	3.00	2.00	3.00	3.00	-	-	-	-	-	-	3.00	3.00	-	3.00	3.00
		CO5	3.00	3.00	2.00	3.00	3.00	-	-	-	-	-	-	3.00	3.00	-	3.00	3.00
		CO6	3.00	3.00	2.00	3.00	3.00	1.00	1.00	1.00	-	-	1.00	3.00	3.00	2.00	3.00	3.00
			2.67	**2.67**	**2.00**	**2.83**	**2.67**	**1.00**	**1.00**	**1.00**	**-**	**-**	**1.00**	**2.67**	**2.83**	**2.00**	**3.00**	**3.00**
SDS511	**Statistical Quality Control**	**CO1**	2.00	3.00	2.00	2.00	2.00	-	1.00	-	-	-	2.00	3.00	2.00	-	2.00	3.00
		CO2	3.00	3.00	3.00	3.00	3.00	1.00	1.00	2.00	-	-	2.00	3.00	3.00	-	2.00	3.00
		CO3	3.00	3.00	3.00	3.00	3.00	-	-	-	-	-	2.00	3.00	3.00	2.00	2.00	3.00
		CO4	3.00	3.00	3.00	3.00	2.00	2.00	2.00	2.00	2.00	2.00	3.00	3.00	3.00	-	2.00	2.00
		CO5	3.00	3.00	3.00	3.00	3.00	2.00	2.00	2.00	1.00	1.00	3.00	3.00	3.00	-	2.00	3.00
		CO6	2.00	2.00	3.00	2.00	3.00	1.00	1.00	-	2.00	2.00	3.00	2.00	2.00	2.00	2.00	2.00
			2.67	**2.83**	**2.83**	**2.67**	**2.67**	**1.40**	**1.40**	**2.00**	**1.67**	**1.67**	**2.50**	**3.00**	**2.67**	**2.00**	**2.00**	**2.67**
SDS512	**Statistical Genetics**	**CO1**	2.00	2.00	3.00	2.00	2.00	1.00	1.00	1.00	1.00	1.00	1.00	2.00	2.00	1.00	2.00	3.00
		CO2	2.00	2.00	3.00	3.00	3.00	1.00	2.00	2.00	2.00	1.00	1.00	2.00	3.00	2.00	3.00	3.00
		CO3	3.00	3.00	3.00	3.00	3.00	2.00	2.00	3.00	2.00	1.00	2.00	3.00	3.00	2.00	3.00	3.00
		CO4	3.00	3.00	3.00	3.00	3.00	2.00	2.00	3.00	2.00	1.00	2.00	3.00	3.00	3.00	3.00	3.00
		CO5	3.00	3.00	3.00	3.00	3.00	2.00	2.00	3.00	2.00	1.00	2.00	3.00	3.00	3.00	3.00	3.00
			2.60	**2.60**	**3.00**	**2.80**	**2.80**	**1.60**	**1.80**	**2.40**	**1.80**	**1.00**	**1.60**	**2.60**	**2.80**	**2.20**	**2.80**	**3.00**
MTH502	**Cryptography and Network Security**	**CO1**	1.00	2.00	1.00	2.00	2.00	1.00	1.00	1.00	2.00	1.00	1.00	2.00	2.00	1.00	2.00	3.00
		CO2	2.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	2.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO3	2.00	3.00	2.00	3.00	2.00	1.00	2.00	2.00	3.00	1.00	2.00	3.00	3.00	2.00	2.00	3.00
		CO4	2.00	3.00	2.00	3.00	2.00	1.00	2.00	2.00	2.00	1.00	2.00	3.00	3.00	2.00	2.00	3.00
		CO5	3.00	3.00	3.00	3.00	3.00	2.00	2.00	3.00	3.00	2.00	3.00	3.00	3.00	2.00	2.00	3.00
		CO6	2.00	3.00	2.00	3.00	2.00	1.00	1.00	2.00	2.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
			2.00	**2.83**	**2.00**	**2.83**	**2.17**	**1.17**	**1.50**	**2.00**	**2.33**	**1.17**	**1.67**	**2.83**	**2.83**	**1.83**	**2.00**	**3.00**

CSE584	**Cloud Computing**	**CO1**	-	-	-	3.00	1.00	-	-	-	-	-	-	1.00	2.00	-	2.00	3.00
		CO2	-	-	2.00	3.00	-	-	-	1.00	-	-	-	2.00	2.00	1.00	2.00	3.00
		CO3	-	1.00	-	3.00	1.00	2.00	-	1.00	-	-	-	2.00	2.00	3.00	2.00	2.00
		CO4	-	-	2.00	2.00	-	-	2.00	2.00	-	-	-	2.00	3.00	2.00	3.00	3.00
		CO5	-	2.00	2.00	3.00	-	-	1.00	-	-	-	-	3.00	3.00	2.00	3.00	3.00
		CO6	-	-	1.00	-	1.00	-	-	1.00	2.00	2.00	3.00	-	1.00	-	-	2.00
			-	**1.50**	**1.75**	**2.80**	**1.00**	**2.00**	**1.50**	**1.25**	**2.00**	**2.00**	**3.00**	**2.00**	**2.17**	**2.00**	**2.40**	**2.67**
SDS513	**Natural Language Processing**	**CO1**	1.00	3.00	2.00	3.00	2.00	1.00	2.00	2.00	1.00	1.00	1.00	2.00	2.00	2.00	2.00	3.00
		CO2	2.00	3.00	2.00	3.00	3.00	2.00	2.00	2.00	2.00	1.00	1.00	3.00	3.00	2.00	3.00	3.00
		CO3	2.00	3.00	2.00	3.00	3.00	2.00	2.00	3.00	2.00	1.00	2.00	3.00	3.00	2.00	2.00	3.00
		CO4	3.00	3.00	2.00	3.00	3.00	2.00	2.00	3.00	2.00	1.00	2.00	3.00	3.00	3.00	2.00	3.00
		CO5	2.00	3.00	2.00	3.00	3.00	1.00	2.00	2.00	2.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO6	3.00	3.00	2.00	3.00	3.00	3.00	3.00	3.00	2.00	1.00	2.00	3.00	3.00	3.00	3.00	3.00
			2.17	**3.00**	**2.00**	**3.00**	**2.83**	**1.83**	**2.17**	**2.50**	**1.83**	**1.00**	**1.50**	**2.83**	**2.83**	**2.33**	**2.33**	**3.00**
SDS514	**Reliability Theory**	**CO1**	2.00	2.00	2.00	2.00	2.00	-	-	-	-	2.00	1.00	2.00	2.00	-	2.00	3.00
		CO2	2.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	2.00	3.00	-	3.00	3.00
		CO3	3.00	3.00	2.00	3.00	2.00	-	-	-	-	-	1.00	3.00	3.00	-	3.00	3.00
		CO4	3.00	3.00	2.00	3.00	2.00	-	-	-	-	-	-	3.00	3.00	-	3.00	3.00
		CO5	3.00	3.00	2.00	3.00	2.00	-	-	-	-	-	1.00	2.00	3.00	-	3.00	3.00
		CO6	3.00	3.00	2.00	3.00	3.00	1.00	1.00	1.00	-	-	1.00	3.00	3.00	2.00	3.00	3.00
			2.67	**2.83**	**2.00**	**2.83**	**2.17**	**1.00**	**1.00**	**1.00**	**-**	**2.00**	**1.00**	**2.50**	**2.83**	**2.00**	**2.83**	**3.00**
SDS515	**Clinical Trials and Biostatistics**	**CO1**	2.00	2.00	2.00	2.00	2.00	-	-	-	-	-	2.00	2.00	2.00	-	2.00	3.00
		CO2	3.00	3.00	2.00	3.00	3.00	-	-	-	-	-	2.00	2.00	3.00	2.00	2.00	3.00
		CO3	3.00	3.00	2.00	3.00	3.00	1.00	1.00	-	-	-	2.00	2.00	3.00	2.00	3.00	3.00
		CO4	3.00	3.00	2.00	3.00	3.00	-	1.00	-	-	-	1.00	3.00	3.00	-	3.00	3.00
		CO5	3.00	3.00	3.00	3.00	3.00	1.00	2.00	1.00	-	1.00	3.00	2.00	3.00	2.00	3.00	3.00
		CO6	3.00	3.00	3.00	3.00	3.00	1.00	2.00	2.00	2.00	1.00	3.00	2.00	3.00	2.00	3.00	3.00
			2.83	**2.83**	**2.33**	**2.83**	**2.83**	**1.00**	**1.50**	**1.50**	**2.00**	**1.00**	**2.17**	**2.17**	**2.83**	**2.00**	**2.67**	**3.00**

SDS516	**Demography**	**CO1**	2.00	2.00	2.00	2.00	2.00	-	-	-	-	2.00	2.00	2.00	2.00	-	2.00	3.00
		CO2	2.00	2.00	2.00	3.00	2.00	-	-	-	-	2.00	2.00	2.00	3.00	-	3.00	3.00
		CO3	2.00	3.00	3.00	3.00	2.00	-	-	-	-	2.00	2.00	2.00	3.00	-	3.00	3.00
		CO4	3.00	3.00	3.00	3.00	3.00	-	1.00	-	-	2.00	2.00	3.00	3.00	-	3.00	3.00
		CO5	3.00	3.00	2.00	3.00	3.00	-	1.00	-	-	-	2.00	3.00	3.00	-	3.00	3.00
		CO6	3.00	3.00	2.00	3.00	3.00	1.00	2.00	1.00	1.00	2.00	3.00	2.00	3.00	-	2.00	3.00
			2.50	**2.67**	**2.33**	**2.83**	**2.50**	**1.00**	**1.33**	**1.00**	**1.00**	**2.00**	**2.17**	**2.33**	**2.83**	**-**	**2.67**	**3.00**
CSE582	**Big Data Analytics**	**CO1**	-	-	-	-	1.00	-	-	-	-	-	-	-	-	1.00	2.00	3.00
		CO2	-	-	-	-	1.00	-	-	-	-	-	-	2.00	-	-	2.00	3.00
		CO3	-	-	-	-	2.00	-	2.00	2.00	-	-	-	3.00	2.00	3.00	3.00	3.00
		CO4	-	-	-	-	2.00	-	2.00	2.00	-	-	-	3.00	3.00	2.00	2.00	3.00
		CO5	-	-	-	-	2.00	2.00	1.00	2.00	-	-	-	3.00	2.00	3.00	3.00	3.00
		CO6	-	-	-	-	2.00	-	2.00	2.00	2.00	-	-	3.00	3.00	2.00	2.00	2.00
			-	**-**	**-**	**-**	**1.67**	**2.00**	**1.75**	**2.00**	**2.00**	**-**	**-**	**2.80**	**2.50**	**2.20**	**2.33**	**2.83**
CSE583	**Cyber Security for Data Science**	**CO1**	3.00	3.00	2.00	3.00	3.00	2.00	2.00	2.00	2.00	-	2.00	3.00	3.00	2.00	2.00	3.00
		CO2	3.00	3.00	2.00	3.00	3.00	2.00	2.00	2.00	2.00	1.00	2.00	3.00	3.00	2.00	2.00	3.00
		CO3	3.00	3.00	2.00	3.00	3.00	2.00	2.00	2.00	2.00	-	2.00	3.00	3.00	2.00	2.00	3.00
		CO4	2.00	2.00	2.00	2.00	2.00	2.00	3.00	2.00	3.00	2.00	3.00	2.00	2.00	2.00	2.00	2.00
		CO5	3.00	3.00	2.00	3.00	3.00	3.00	2.00	3.00	2.00	-	2.00	3.00	3.00	3.00	2.00	3.00
			2.80	**2.80**	**2.00**	**2.80**	**2.80**	**2.20**	**2.20**	**2.20**	**2.20**	**1.50**	**2.20**	**2.80**	**2.80**	**2.20**	**2.00**	**2.75**
SDS517	**Image Processing and Computer Vision**	**CO1**	2.00	3.00	2.00	3.00	2.00	1.00	2.00	2.00	1.00	1.00	1.00	3.00	2.00	1.00	2.00	3.00
		CO2	1.00	2.00	1.00	2.00	2.00	2.00	3.00	2.00	2.00	1.00	1.00	2.00	2.00	1.00	3.00	2.00
		CO3	3.00	3.00	2.00	3.00	3.00	1.00	2.00	2.00	1.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO4	2.00	3.00	2.00	3.00	3.00	2.00	2.00	3.00	1.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO5	2.00	3.00	2.00	3.00	3.00	2.00	2.00	2.00	1.00	1.00	1.00	3.00	3.00	2.00	2.00	3.00
		CO6	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	2.00	2.00	2.00	3.00	3.00	3.00	3.00	3.00
			2.17	**2.83**	**2.00**	**2.83**	**2.67**	**1.83**	**2.33**	**2.33**	**1.33**	**1.17**	**1.17**	**2.83**	**2.67**	**1.83**	**2.33**	**2.83**
SDS518	**Tools and Techniques for Research Writing**	**CO1**	1.00	2.00	1.00	2.00	2.00	1.00	2.00	1.00	1.00	-	-	2.00	2.00	1.00	2.00	2.00
		CO2	2.00	3.00	2.00	2.00	2.00	2.00	3.00	2.00	1.00	1.00	1.00	3.00	2.00	2.00	2.00	2.00
		CO3	2.00	3.00	2.00	3.00	2.00	1.00	2.00	2.00	1.00	-	-	2.00	3.00	2.00	3.00	3.00
		CO4	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.00	-	2.00	2.00	2.00	2.00	2.00
			1.75	**2.50**	**1.75**	**2.25**	**2.00**	**1.50**	**2.25**	**1.75**	**1.25**	**1.00**	**1.00**	**2.25**	**2.25**	**1.75**	**2.25**	**2.25**