MANIPAL
ACADEMY of HIGHER EDUCATION
(Deemed to be University under Section 3 of the UGC Act, 1956)

Manipal School of Information Sciences

Manipal Academy of Higher Education, Manipal

Outcome Based Education (OBE) Framework

Two Year full time Postgraduate Program

Master of Engineering - ME (Artificial Intelligence and Machine Learning)

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NATURE AND EXTENT OF THE PROGRAM

Artificial Intelligence and Machine Learning are shaping the world around us and will play a ubiquitous role in diverse fields in the future. There is an ever-increasing industrial demand for professionals equipped with solid mathematical, computational, and coding skills who can play an integral role in applying Machine Learning skills to real-life problems. The ME in Machine Learning Program is a post-graduate program aimed at producing highly skilled Machine Learning Engineers who can adapt to the rapidly advancing field. The Program has a comprehensive mix of fundamental mathematical and practical skills that offer the graduates highly rewarding career opportunities.

Students will acquire solid mathematical and computational skills essential for understanding, applying, and developing modern machine learning algorithms. They will be able to identify appropriate and efficient algorithmic approaches for solving real-life problems using machine learning principles and state of the art software prevalent in industry and academia. Through ethical practices, teamwork, and leadership skills, students will use machine learning skills to address problems of social importance for sustainable societal development.

The program offers opportunity to work as Data Scientist, Machine Learning Engineer, Data Engineer, Software Developer, and Entrepreneurs.

PROGRAM EDUCATION OBJECTIVE (PEO)

The overall objectives of the Learning Outcomes-based Curriculum Framework (LOCF) for the **ME (Artificial Intelligence and Machine Learning) program are as follows:**

PEO No	Education Objective
1	Produce industry-ready graduates with solid foundation in fundamentals of machine learning and practical experience in structuring machine learning projects using state of the art software.
2	Machine learning researchers who can innovate and address research challenges through doctoral studies and professional roles in public/private research labs.
3	Entrepreneurial engineers who can identify and address real-life problems in sustainability, environment, education, and governance.

GRADUATE ATTRIBUTES

S No.	Attribute	Description
1	**Scholarship of Knowledge**	Acquire in-depth knowledge of specific discipline or professional area, including wider and global perspective, with an ability to discriminate, evaluate, analyse and synthesise existing and new knowledge, and integration of the same for enhancement of knowledge.
2	**Critical Thinking**	Analyse complex engineering problems critically, apply independent judgement for synthesising information to make intellectual and/or creative advances for conducting research in a wider theoretical, practical and policy context.
3	**Problem Solving**	Think laterally and originally, conceptualise and solve engineering problems, evaluate a wide range of potential solutions for those problems and arrive at feasible, optimal solutions after considering public health and safety, cultural, societal and environmental factors in the core areas of expertise.
4	**Research Skill**	Extract information pertinent to unfamiliar problems through literature survey and experiments, apply appropriate research methodologies, techniques and tools, design, conduct experiments, analyse and interpret data, demonstrate higher order skill and view things in a broader perspective, contribute individually/in group(s) to the development of scientific/technological knowledge in one or more domains of engineering.
5	**Usage of modern tools**	Create, select, learn and apply appropriate techniques, resources, and modern engineering and IT tools, including prediction and modelling, to complex engineering activities with an understanding of the limitations.
6	**Collaborative and Multidisciplinary work**	Possess knowledge and understanding of group dynamics, recognise opportunities and contribute positively to

		collaborative-multidisciplinary scientific research, demonstrate a capacity for self-management and teamwork, decision-making based on open-mindedness, objectivity and rational analysis to achieve common goals and further the learning of themselves as well as others.
7	**Project Management and Finance**	Demonstrate knowledge and understanding of engineering and management principles and apply the same to one's own work, as a member and leader in a team, manage projects efficiently in respective disciplines and multidisciplinary environments after consideration of economic and financial factors.
8	**Communication**	Communicate with the engineering community, and with society at large, regarding complex engineering activities confidently and effectively, such as, being able to comprehend and author effective reports and design documentation by adhering to appropriate standards, make effective presentations, and give and receive clear instructions.
9	**Life-long Learning**	Recognise the need for and have the preparation and ability to engage in life-long learning independently, with a high level of enthusiasm and commitment to improve knowledge and competence continuously.
10	**Ethical Practices and Social Responsibility**	Acquire professional and intellectual integrity, professional code of conduct, ethics of research and scholarship, consideration of the impact of research outcomes on professional practices and an understanding of responsibility to contribute to the community for sustainable development of society.
11	**Independent and Reflective Learning**	Observe and examine critically the outcomes of one's actions and make corrective measures subsequently and learn from mistakes without depending on external feedback.

QUALIFICATIONS DESCRIPTORS

1. Demonstrate:

   (i) systematic, extensive, and coherent knowledge and understanding of machine learning and its applications, and links to related areas/subjects of study; including a critical understanding of the established theories, principles and concepts, and of several advanced and emerging issues in the field of machine learning.

   (ii) procedural knowledge that creates diverse types of professionals related to machine learning, including research and development, teaching, and government and public service.

   (iii) professional communication skills in the domains of machine learningand artificial intelligence including a critical understanding of the latest developments and computing tools.

2. Demonstrate comprehensive knowledge about materials, including current research, scholarly, and/or professional literature, relating to essential and advanced learning areas pertaining to machine learning, and techniques and skills required for identifying problems and related issues.
3. Demonstrate skills in identifying information needs, collection of relevant quantitative and/or qualitative data drawing on a wide range of sources, analysis and interpretation of data.
4. Demonstrate skills in identifying methodologies for formulating evidence-based solutions and arguments.
5. Use knowledge, understanding, and skills for critical assessment of a wide range of ideas, complex problems and issues related to machine learning.
6. Communicate the results of studies undertaken accurately and unambiguously.
7. Address one's own learning needs relating to current and emerging areas of study, making use of research, development, and professional materials as appropriate, including those related to new frontiers of knowledge.
8. Apply one's disciplinary knowledge and transferable skills to new/unfamiliar contexts, identify and analyse real-life problems, and seek novel solutions.

PROGRAM OUTCOMES

After successful completion of ME (Artificial Intelligence and Machine Learning), students will be able to:

PO No	Attribute	Competency
1	**Scholarship of Knowledge**	Acquire solid mathematical and computational skills essential for understanding, applying, and developing modern machine learning algorithms.
2	**Critical Thinking**	Identify, formulate, analyse, and solve real-life problems using machine learning principles.
3	**Problem Solving**	Identify appropriate and efficient algorithmic approaches for solving real-life problems using machine learning principles.
4	**Research Skill**	Keep updated with current research trends in machine learning and innovate research ideas for developing new machine learning paradigms.
5	**Usage of Modern Tools**	Gain solid skills in using state of the art modern machine learning software prevalent in industry and academia.
6	**Collaborative and Multidisciplinary Work**	Use machine learning as a common solution platform to identify problems and collaborate with researchers from health care, natural & social sciences, arts, and humanities.
7	**Project Management and Finance**	Streamline and realize project ideas into entrepreneurial ventures involving good project management practices and financial considerations.
8	**Communication**	Professionally communicate the results of applying machine learning algorithms to real life problems to aid decision making processes.
9	**Life-long Learning**	Evolve and adapt to the fast-changing artificial intelligence landscape through academic and industrial engagements.
10	**Ethical Practices and Social Responsibility**	Through ethical practices, teamwork, and leadership skills, use machine learning skills to address problems of social importance for sustainable societal development.

11	**Independent and Reflective Learning**	Critically examine data and the interpretation of outcomes of machine learning algorithms and take corrective measures without depending on external feedback.

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COURSE STRUCTURE, COURSEWISE LEARNING OBJECTIVE, AND COURSE OUTCOMES (CO)

FIRST YEAR:

Semester: 1 **Semester: 2**

Subject Code	Subject Title	L	T	P	C	Subject Code	Subject Title	L	T	P	C
BDA 602	Algorithms and Data Structures for Big Data	3	-	-	3	MCL 602	Advanced Applications of Probability & Statistics	3	-	-	3
MCL 601	Applied Probability & Statistics	3	-	-	3	MCL 604	Machine Learning Principles & Applications	3	-	-	3
MCL 603	Applied Linear Algebra	3	-	-	3	MCL 606	Deep Learning	3	-	-	3
MCL 605	Applied Machine Learning	3	-	-	3	MCL 608	Reinforcement Learning	3	-	-	3
	Elective - I	3	-	-	3		Elective - II	3	-	-	3
BDA 602L	Algorithms and Data Structures for Big Data Lab	-	-	3	1	MCL 602L	Advanced Applications of Probability & Statistics Lab	-	-	3	1
MCL 601L	Applied Probability & Statistics Lab	-	-	3	1	MCL 604L	Machine Learning Principles & Applications Lab	-	-	3	1
MCL 603L	Applied Linear Algebra Lab	-	-	3	1	MCL 606L	Deep Learning Lab	-	-	3	1
MCL 605L	Applied Machine Learning Lab	-	-	3	1	MCL 608L	Reinforcement Learning Lab	-	-	3	1
	Elective - I Lab	-	-	3	1		Elective - II Lab	-	-	3	1
MCL 695	Mini Project - I	-	-	4	-	MCL 696	Mini Project - II	-	-	-	4
MCL 697	Seminar - I	-	-	1	-	MCL 698	Seminar - II	-	-	-	1
Total		**15**	**-**	**15**	**25**	**Total**		**15**	**-**	**15**	**25**

SECOND YEAR (FINAL YEAR):

III and IV Semester		
MCL 799	Project Work	25
Total Number of Credits to Award Degree		75

List of Electives (Theory)

Elective - 1		Elective - 2	
Code	**Subject**	**Code**	**Subject**
MCL-615	Applications of Graph Theory	MCL-616	Applied Mathematics for Machine Learning
BDA-622	Principles of Data Visualization	MCL-617	Natural Language Processing Principles & Applications
BDA-623	Architecture of Big Data Systems	MCL-618	Convolutional Neural Networks for Computer Vision
		ENP-601	Entrepreneurship

List of Electives (Lab)

Elective - 1		Elective - 2	
Code	**Subject**	**Code**	**Subject**
MCL-615L	Applications of Graph Theory Lab	MCL-616L	Applied Mathematics for Machine LearningLab
BDA-622L	Principles of Data Visualization Lab	MCL-617L	Natural Language Processing Principles & Applications Lab
BDA-623L	Architecture of Big Data Systems Lab	MCL-618L	Convolutional Neural Networks for Computer Vision Lab
		ENP-601L	Entrepreneurship

Name of the Program:	ME in Machine Learning
Course Title:	Algorithms and Data Structures for Big Data
Course Code: BDA 602	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 1
No of Credits: 3	**Prerequisites:** Programming in Python, C

Synopsis:	This course introduces students to elementary data structures and design of algorithms.Students learn how to design optimal algorithms with respect to time and space; implement link list, stack, queues, searching and sorting techniques, sets, trees and graphs; implement string and text processing techniques; implement data stream algorithms.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Analyse recursive programs, solve a general class of recurrence relations.
CO 2:	Design programs for implementation of linked lists, stack, queues, binary search tree, sorting and searching.
CO 3:	Design programs for dictionary, hash tables, graphs and shortest path techniques.
CO 4:	Design string and text processing programs.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*						*		
CO 2	*	*	*						*		
CO 3	*	*	*						*		
CO 4	*	*	*	*							

Course content and outcomes:

Content	***Competencies***
Unit 1: Algorithm Specification and Analysis Techniques	
Analysis of recursive programs. Solving recurrence equations. General solution for a large class of recurrences.	1. Define recursive programs (C2) 2. Design simple recursive programs (C4) 3. Solve recurrence relations (C4)
Unit 2: Elementary Data Structures	

Implementation of lists, stacks, queues.	1. Design singly linked list (C3) 2. Design doubly linked list(C3) 3. Explain the concepts of array-based stacks (C2) 4. Explain the concepts of pointer-based stacks (C2) 5. Design and implement Queues. (C4)
Unit 3: Sorting and Searching Techniques	
Quick sort, heap sort, merge sort. Linear search and binary search.	Design applications with suitable sorting and searching techniques. (C4)
Unit 4: Hashing and Dictionaries	
Hashing and Dictionaries	Design various hash functions and implement suitable hash tables (C4)
Unit 5: Binary Search Trees	
Construction. In-order, pre-order and post-order traversals.	Understand and implement BST and its various traversal techniques (C2)
Unit 6: Graphs	
Representation of graphs. Depth First Searching. Breadth First Searching. Minimum cost spanning tree. Single source shortest paths and all-pairs shortest path.	1. Define graphs (C2) 2. Design data structure for graphs (C6) 3. Formulate an algorithm to solve minimum cost spanning tree(C6) 4. Formulate an algorithm to solve Single source shortest path (C6) 5. Formulate an algorithm to solve All- pair shortest path(C6)
Unit 7: String and Text Processing Techniques	
Pattern-Matching Algorithms. Text Compression. Tries.	**1.** Design applications with suitable pattern matching algorithms (C4).
Unit 8: Data Stream Algorithms	

Sampling, Random Projections, Basic Algorithmic Techniques Group Testing, Tree Method and Graph sketching.	**1.** Implement suitable data streaming algorithms (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4
Sessional Examination 1	*	*		
Sessional Examination 2		*	*	
Assignment/Presentation				*
End Semester Examination	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback

Reference Material	1. Introduction to Algorithms - Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest. MIT Press. 2. Data Structures and Algorithms - Aho, Hopcroft and Ulmann. Pearson Publishers. 3. Data Structures and Algorithms in Python - Michael T. Goodrich, Roberto Tamassia, and Michael H. Goldwasser. John Wiley & Sons. 4. Data Streams: Algorithms and Applications - S. Muthukrishnan. Foundations and Trends in Theoretical Computer Science archive, Volume 1 Issue 2, August 2005, Pages 117 – 236.

Name of the Program:	ME in Machine Learning
Course Title:	Algorithms and Data Structures for Big Data Lab
Course Code: BDA 602L	**Course Instructor:**
Academic Year:2020-2021	**Semester:** First Year, Semester 1
No of Credits:1	**Prerequisites:**Programming in C or Python
Synopsis:	This course introduces students to elementary data structures and design of algorithms.Students learn how to design optimal algorithms with respect to time and space; implement link list, stack, queues, searching and sorting techniques, sets, trees and graphs; implement string and text processing techniques; implement data stream algorithms.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Evaluate the performance of algorithms.
CO 2:	Develop applications using suitable data structures.
CO 3:	Design applications using data streaming and pattern matching algorithms.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*						*		
CO 2	*	*	*			*					
CO 3	*	*	*		*	*					

Course content and outcomes:

Content	***Competencies***
Unit 1: Elementary Data Structures	
Linked List, Stacks, Queues, Sorting and Searching Techniques	Implement Linked list, Stacks, Queues (C4). Design applications using various searching and Sorting techniques.
Unit 2: Tree, Sets and Hash Table	
Binary Tree, Binary search tree Sets and Hash Tables	Implement Binary Tree and BST (C4). Design applications using Hash Tables
Unit 3: Graph	
Representation of Graph BFS and DFS	Implement Graph and its traversals (BFS, DFS) (C4).

Shortest path algorithms	Design applications with shortest path algorithms (C4).
Unit 4: Pattern Matching and Data streaming	
	Implement pattern matching algorithms (C4).

Learning strategies, contact hours and student learning time		
Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:	
Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos			
Nature of assessment	CO 1	CO 2	CO 3
Sessional Examination 1	*	*	
Sessional Examination 2		*	*

Assignment/Presentation	*	*	*
End Semester Examination	*	*	*
Laboratory Examination	*	*	*
Feedback Process	• Mid-Semester feedback • End-Semester Feedback		
Reference Material	1. Data Structures and Algorithms in Python - Michael T. Goodrich, Roberto Tamassia, and Michael H. Goldwasser. John Wiley & Sons. 2. Data Streams: Algorithms and Applications - S. Muthukrishnan. Foundations and Trends in Theoretical Computer Science archive, Volume 1 Issue 2, August 2005, Pages 117 – 236.		

Name of the Program:	ME in Machine Learning
Course Title:	Applied Probability and Statistics
Name of the Program:	ME in Machine Learning
Academic Year: 2020-2021	**Semester:**First Year, Semester 1
No of Credits: 3	**Prerequisites:**Basic algebra and calculus

Synopsis:	This course introduces fundamental concepts in probability and statistics that are essential for data science applications.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Understand and apply the basic principles of sampling.
CO 2:	Model random phenomena using random variables.
CO 3:	Calculate & interpret probability as a measure of quantifying uncertainty.
CO 4:	Construct Bayesian models for analysing practical problems.
CO 5:	Use sample information and perform hypothesis-test analysis using an appropriate statistical technique to explain attributes of a population.

Mapping of COs to Pos

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2	*	*	*								
CO 3	*	*	*	*				*			
CO 4		*	*	*		*		*			
CO 5		*	*	*		*				*	

Course content and outcomes:

Content	***Competencies***
Unit 1: Counting; Probability Concepts; Conditional Probability	
Multiplication rule; permutation; combination - Sampling: with/without replacement and order matters/does not matter - Binomial & multinomial coefficients - Distribution problems Set theory; sample space; outcomes; events - Frequency based definition of	1. Understand and apply the basic principles of sampling (C1, C3). 2. Understand and apply the basic principles of probability (C1, C3). 3. Differentiate and relate frequency-based interpretation of probability to classical approach (C4).

probability - Equally likely vs. not equally likely outcomes - Axioms of probability Conditional probability; probability tree model; chain rule - Decomposition and the law of total probability - Bayes' rule - intuition, dependence/independence of events.	4. Apply Bayesian principle for modelling practical problems (C5).
Unit 2: Random Variables	
Modelling using discrete random variables: Bernoulli, geometric, binomial, negative binomial, hypergeometric, and Poisson distributions - Probability mass function and cumulative distribution function - Expectation and variance: discrete case - Modelling using continuous random variables: uniform, normal, log-normal, exponential, and beta distributions; probability density function - Expectation and variance: continuous case - Functions of random variables.	1. Understand and differentiate discrete and continuous random variables of practical interest (C2, C4). 2. Gain solid foundation in the mathematical aspects of random variables (C2). 3. Understand how to use random variables to model random phenomena (C4). 4. Compare and contrast practical applicability of random variables (C6).
Unit 3: Sampling and Parameter Estimation	
Population and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem – intuition and applications Point estimation - Standard error - Interval estimation: interpretation of confidence interval - Hypothesis testing: p-values, significance level and their interpretations, application to	1. Differentiate population and sample (C4). 2. Describe population parameters using inferences drawn from a sample (C6). 3. Design and apply appropriate hypothesis tests for practical problems (C3). 4. Communicate and explain the results of hypothesis testing (C6).

analysis of one- /two-sample mean and paired data.	

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Introduction to Probability, Charles M. Grinstead, American Mathematical Society; 2nd Revised Edition 1997. Available online at

	https://open.umn.edu/opentextbooks/textbooks/introduction-to-probability 2. A First Course in Probability, Sheldon Ross, 9th Edition, Pearson Education India; 9th Edition, 2013. 3. Biostatistics Open Learning textbook – Online resource from University of Florida available at https://bolt.mph.ufl.edu/6050-6052/ 4. All of Statistics: A Concise Course in Statistical Inference, Larry Wasserman – Springer.

Name of the Program:	ME in Machine Learning
Course Title:	Applied Probability and Statistics Lab
Course Code:MCL 601L	**Course Instructor:**

Academic Year: 2020-2021	**Semester:**First Year, Semester 1
No of Credits: 1	**Prerequisites:**MCL 601

Synopsis:	This course provides a hands-on introduction to fundamental concepts in probability and statistics that are essential for data science applications using the R programming language.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Apply the basic principles of sampling to practical problems.
CO 2:	Visualize probability concepts through frequency-based interpretations.
CO 3:	Simulate discrete and continuous random variables for modelling random phenomena.
CO 4:	Design and apply hypothesis tests followed by interpretation of results.
CO 5:	Interpret statistical results and communicate them unambiguously and effectively.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*		*						
CO 2		*	*		*						
CO 3	*	*	*	*	*						
CO 4		*	*	*	*	*					
CO 5				*	*	*		*		*	

Course content and outcomes:

Content	*Competencies*
Unit 1: Counting; Probability Concepts; Conditional Probability	
Multiplication rule; permutation; combination - Sampling: with/without replacement and order matters/does not matter - Binomial & multinomial coefficients - Distribution problems Set theory; sample space; outcomes; events - Frequency based definition of	1. Understand the basic principles of the R programming language (C1). 2. Develop short code snippets to understand the basic principles of sampling and probability (C1, C3). 3. Visualise and interpret probability concepts through a frequency-based approach (C6).

probability - Equally likely vs. not equally likely outcomes - Axioms of probability Conditional probability; probability tree model; chain rule - Decomposition and the law of total probability - Bayes' rule - intuition, dependence/independence of events.	4. Program and analyse Bayesian models for practical problems (C4).
Unit 2: Random Variables	
Modelling using discrete random variables: Bernoulli, geometric, binomial, negative binomial, hypergeometric, and Poisson distributions - Probability mass function and cumulative distribution function - Expectation and variance: discrete case - Modelling using continuous random variables: uniform, normal, log-normal, exponential, and beta distributions; probability density function - Expectation and variance: continuous case - Functions of random variables.	1. Understand and apply R functions to simulate discrete and continuous random variables (C3). 2. Using sampling, compute and interpret different attributes of random variables (C4). 3. Visualise and interpret histograms and probability mass/density functions of random variables using state of the art visualisation libraries in R (C4). 4. Develop codes to model random phenomena using appropriate random variables (C5).
Unit 3: Sampling and Parameter Estimation	
Population and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem – intuition and applications Point estimation - Standard error - Interval estimation: interpretation of confidence interval - Hypothesis testing: p-values, significance level and their interpretations, application to	1. Visualise sample data through histograms (C3). 2. Compute estimates of population parameters using samples and communicate the uncertainty in the estimates (C4). 3. Use R in-built functions for performing hypothesis tests (C4). 4. Interpret and communicate the results of hypothesis tests (C6).

analysis of one- /two-sample mean and paired data	

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback

	• End-Semester Feedback
Reference Material	1. Introduction to Probability, Charles M. Grinstead, American Mathematical Society; 2nd Revised Edition 1997. Available online at https://open.umn.edu/opentextbooks/textbooks/introduction-to-probability 2. A First Course in Probability, Sheldon Ross, 9th Edition, Pearson Education India; 9th Edition, 2013. 3. Biostatistics Open Learning textbook – Online resource from University of Florida available at https://bolt.mph.ufl.edu/6050-6052/ 4. All of Statistics: A Concise Course in Statistical Inference, Larry Wasserman – Springer.

Name of the Program:	ME in Machine Learning
Course Title:	Applied Linear Algebra
Course Code:MCL 603	**Course Instructor:**
Academic Year: 2020-2021	**Semester:**First Year, Semester 1
No of Credits: 3	**Prerequisites:**Basic algebra and calculus

Synopsis:	This course introduces fundamental concepts in probability and statistics that are essential for data science applications.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Understand how to use vectors and matrices to model real-life quantities.
CO 2:	Develop a solid understanding of matrix-vector operations and relate them to real-life calculations.
CO 3:	Apply and analyse algorithms constructed using matrix-vector principles.
CO 4:	Develop models for real-life applications using the least squares technique and interpret the results from a practical perspective.
CO 5:	Develop a solid foundation for extending matrix-vector principles to modern machine learning algorithms.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2	*	*									
CO 3	*	*	*	*	*			*			
CO 4		*	*	*	*	*		*			
CO 5		*	*	*	*	*					

Course content and outcomes:

Content	***Competencies***
Unit 1: Vectors	
Conceptual introduction to vectors; vector addition; scalar-vector multiplication - Dot product; norm; distance - Standard deviation; standardization vs. normalization; angle between vectors - Application example: k-means clustering algorithm - Linear dependence/independence; basis -	1. Understand the mathematical language behind vectors and compare algebraic and geometric representations of vectors (C2, C4). 2. Understand mathematical operations involving vectors and their applications in real-life (C2, C3). 3. Construct a clustering algorithm from scratch using vector principles and operations (C5).

Orthonormal vectors; projections; Gram-Schmidt algorithm.	4. Gain a solid understanding of important theoretical principles to be applied later (C2).
Unit 2: Matrices	
Conceptual introduction to matrices; types of matrices (zero, identity, diagonal) - Addition of matrices; transpose; norm - Matrix-vector product – concept & examples - Systems of linear equations: over- & under-determined systems - Matrix-matrix product – concept & examples - QR factorization - Solving linear equations.	1. Understand the mathematical language behind matrices and interpret them as extensions of vectors (C2, C6). 2. Understand mathematical operations involving matrices & vectors and their applications in real-life (C2, C3). 3. Gain a solid understanding of important theoretical principles involved in solving systems of linear equations (C2). 4. Develop and interpret matrix factorization as a powerful tool for data analysis (C5, C6).
Unit 3: Linear Least Squares	
Least squares: problem motivation and examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification	1. Understand the mathematical setup of a linear least squares problem using practical examples (C2). 2. Formulate linear least squares problem using block matrix operations (C5). 3. Understand how to select good features for data fitting using least squares (C2, C6). 4. Construct and compare least squares classification with regression (C5, C6).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04

Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Introduction to Applied Linear Algebra, Vectors, Matrices, and Least Squares, Stephen Boyd & Lieven Vandenberghe, Cambridge University Press, 1st Edition, 2018. Available online at http://vmls-book.stanford.edu/vmls.pdf 2. Linear Algebra and its Applications, Gilbert Strang, CENGAGE LEARNING (RS); 4th Edition, 2005. 3. Matrix Methods: Applied Linear Algebra, Richard Bronson and Gabriel B. Costa, Academic Press; 3rd Edition, 2008. 4. Matrix Methods in Data Mining and Pattern Recognition (Fundamentals of Algorithms), Lars Eldén – Society for Industrial and Applied Mathematics, 2007.

Name of the Program:	ME in Machine Learning
Course Title:	Applied Linear Algebra Lab
Course Code:MCL 603L	**Course Instructor:**
Academic Year: 2020-2021	**Semester:**First Year, Semester 1

No of Credits: 1	**Prerequisites:** MCL 603
Synopsis:	This course provides a hands-on introduction to fundamental concepts in linear algebra that are essential for data science applications using the Python programming language.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Develop solid skills in using Python's legacy libraries for coding matrix-vector operations
CO 2:	Implement algorithms constructed using matrix-vector principles.
CO 3:	Implement models for real-life applications using the least squares technique and interpret the results from a practical perspective.

Mapping of COs to Pos

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*									
CO 2		*	*	*	*						
CO 3	*	*	*	*	*	*					

Course content and outcomes:

Content	*Competencies*
Unit 1: Vectors	
Conceptual introduction to vectors; vector addition; scalar-vector multiplication - Dot product; norm; distance - Standard deviation; standardization vs. normalization; angle between vectors - Application example: k-means clustering algorithm - Linear dependence/independence; basis - Orthonormal vectors; projections; Gram-Schmidt algorithm.	1. Understand how to perform vector operations using Python (C2). 2. Visualize vectors and relate them to their geometric description (C1, C2). 3. Implement the K-means algorithm from scratch using vector operations (C5). 4. Implement and interpret the output of the Gram-Schmidt algorithm (C5).
Unit 2: Matrices	

Conceptual introduction to matrices; types of matrices (zero, identity, diagonal) - Addition of matrices; transpose; norm - Matrix-vector product – concept & examples - Systems of linear equations: over- & under-determined systems - Matrix-matrix product – concept & examples - QR factorization - Solving linear equations.	1. Understand how to perform matrix operations using Python (C2). 2. Implement and interpret matrix-vector operations using block-matrix operations (C5). 3. Understand how to solve linear systems of equations using Python (C2). 4. Code practical applications of QR factorization of matrices (C4).
Unit 3: Linear Least Squares	
Least squares: problem motivation and examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification	1. Solve linear least squares problems using Python and interpret the results (C3). 2. Implement and fine-tune feature extraction using least squares for practical problems (C5). 3. Implement least squares classification (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	-

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos					
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Introduction to Applied Linear Algebra, Vectors, Matrices, and Least Squares, Stephen Boyd & Lieven Vandenberghe, Cambridge University Press, 1st Edition, 2018. Available online at http://vmls-book.stanford.edu/vmls.pdf 2. Linear Algebra and its Applications, Gilbert Strang, CENGAGE LEARNING (RS); 4th Edition, 2005. 3. Matrix Methods: Applied Linear Algebra, Richard Bronson and Gabriel B. Costa, Academic Press; 3rd Edition, 2008. 4. Matrix Methods in Data Mining and Pattern Recognition (Fundamentals of Algorithms), Lars Eldén – Society for Industrial and Applied Mathematics, 2007.

Name of the Program:	ME in Machine Learning
Course Title:	Applied Machine Learning
Course Code:MCL 605	**Course Instructor:**
Academic Year: 2020-2021	**Semester:**First Year, Semester 1
No of Credits: 3	**Prerequisites:**Python programming

Synopsis:	This course provides a broad introduction to important concepts and algorithms in applied machine learning.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Develop practical experience with state-of-the-art machine learning tools and libraries.
CO 2:	Differentiate between different types of machine learning paradigms and choose an appropriate one for a given application problem.
CO 3:	Apply different types of supervised and unsupervised machine learning algorithms to practical problems and assess their performance.
CO 4:	Understand the importance of feature engineering in machine learning applications.
CO 5:	Acquire a solid foundation in basic machine learning skills for more advanced expositions.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*				*						
CO 2	*	*	*	*							
CO 3	*	*	*	*		*		*			
CO 4		*	*	*		*				*	
CO 5	*	*	*	*					*		

Course content and outcomes:

Content	*Competencies*
Unit 1: Introduction to Machine Learning; Introduction to Supervised Learning; Decision Trees	
Overview of Supervised (regression and classification), unsupervised (clustering and dimensionality reduction), semi-supervised, and reinforcement learning with practical examples - Machine	1. Gain a basic understanding of different types of problems and nomenclature in machine learning (C2). 2. Understand and interpret results of cross validation in machine learning through a simple algorithm (C2, C3).

learning nomenclature: raw data, types of features and outputs, feature vector. Computing distances and similarities - Prototype based classification - K-nearest neighbours - Over- and under-fitting -Introduction to cross validation Decision tree model of learning - Classification and regression using decision trees - Splitting criteria: entropy, information gain, Gini impurity - Building a decision tree	3. Understand the decision tree learning model and splitting criteria (C2). 4. Compare and contrast classification vs. regression using decision trees (C4).
Unit 2: Linear Models; Feature Selection; Introduction to Unsupervised Learning	
Linear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance trade-off - Regularized linear regression Filter, wrapper, and embedded methods Clustering vs. classification - Hierarchical clustering: dendogram construction, types of linkage - Dimension reduction using principal component analysis (PCA)	1. Understand the basics of linear models for regression and classification, interpret results and coefficients (C4). 2. Differentiate feature selection approaches in machine learning (C4). 3. Understand the working principle behind hierarchical clustering (C2). 4. Visualize the mathematical setup behind PCA and compare the matrix-factorization vs. projection-error-minimisation approaches (C4, C5).
Unit 3: Probabilistic Models for Supervised Learning; Support Vector Machine; Ensemble Methods	

Probabilistic modelling of data using parameters - Introduction to maximum likelihood estimation (MLE) of parameters - Naive Bayes model for classification - Logistic regression for binary classification Classification using linear SVM - Dealing with nonlinearly separable data Bagging: classification using random forest - Boosting	1. Formulate maximum likelihood estimation of model parameters (C5). 2. Understand the probabilistic principles behind Naive Bayes and Logistic Regression algorithms (C2). 3. Formulate the SVM mathematical model and interpret algorithm parameters and results (C5). 4. Develop intuition and ideas behind ensemble algorithms for machine learning (C5).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			

Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Grokking Machine Learning, Luis G. Serrano, Manning Publications; 1st Edition, 2019. Online resource from Manning Publications available at https://www.manning.com/books/grokking-machine-learning 2. A Course in Machine Learning, Hal Daumé III – Online resource available at http://ciml.info/ 3. An Introduction to Statistical Learning with Applications in R, Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, Springer; 1st Edition, 2013, Corr. 7th printing 2017 Edition. 4. Mathematics for Machine Learning, Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong – Online resource from Cambridge University Press available at https://mml-book.github.io/book/mml-book.pdf.

Name of the Program:	ME in Machine Learning
Course Title:	Applied Machine Learning Lab
Course Code:MCL 605L	**Course Instructor:**
Academic Year: 2020-2021	**Semester:**First Year, Semester 1
No of Credits: 1	**Prerequisites:**MCL 605**,** Python programming

Synopsis:	This course provides a coding-based introduction to important concepts and algorithms in applied machine learning using Python.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Develop codes using state of the art machine learning tools and libraries.
CO 2:	Code different types of machine learning paradigms and choose an appropriate one for a given application problem.
CO 3:	Code different types of supervised and unsupervised machine learning algorithms to practical problems and assess their performance.
CO 4:	Implement and explore feature engineering approaches in machine learning applications.
CO 5:	Acquire a solid foundation in coding skills for more advanced applications of machine learning.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*		*	*	*						
CO 2	*	*	*	*	*						
CO 3	*	*	*	*	*	*		*			
CO 4		*	*	*	*	*				*	
CO 5	*	*	*	*	*				*		

Course content and outcomes:

Content	***Competencies***
Unit 1: Introduction to Machine Learning; Introduction to Supervised Learning; Decision Trees	
Overview of Supervised (regression and classification), unsupervised (clustering and dimensionality reduction), semi-supervised, and reinforcement learning with practical examples - Machine learning nomenclature: raw data, types of features and outputs, feature vector.	1. Program data, perform data wrangling, understand the data matrix, and differentiate between sample and feature (C2, C4). 2. Investigate over- and underfitting concepts using the K-nearest neighbour algorithm (C3). 3. Implement and interpret results of cross-validation (C3).

Computing distances and similarities - Prototype based classification - K-nearest neighbours - Over- and under-fitting -Introduction to cross validation Decision tree model of learning - Classification and regression using decision trees - Splitting criteria: entropy, information gain, Gini impurity - Building a decision tree	4. Implement decision tree models in Python, fine-tune model parameters, and interpret results (C4).
Unit 2: Linear Models; Feature Selection; Introduction to Unsupervised Learning	
Linear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance trade-off - Regularized linear regression Filter, wrapper, and embedded methods Clustering vs. classification - Hierarchical clustering: dendogram construction, types of linkage - Dimension reduction using principal component analysis (PCA)	1. Implement linear models in Python and interpret model coefficients for practical problems. 2. Implement and visualize bias-variance trade-off using linear regression as a basis (C4). 3. Compare, and contrast different feature engineering approaches for practical problems (C4). 4. Visualize the output of hierarchical clustering and PCA algorithms and interpret the results (C4).
Unit 3: Probabilistic Models for Supervised Learning; Support Vector Machine; Ensemble Methods	
Probabilistic modelling of data using parameters - Introduction to maximum likelihood estimation (MLE) of	1. Implement maximum likelihood estimation for a simple model (C4).

parameters - Naive Bayes model for classification - Logistic regression for binary classification Classification using linear SVM - Dealing with nonlinearly separable data Bagging: classification using random forest - Boosting	2. Analyse the performance of the Naive Bayes model for practical problems (C4). 3. Apply the SVM algorithm for linearly- and not-linearly separable data, compare the performance (C5). 4. Through coding, understand how ensemble methods in machine learning work (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

MANIPAL ACADEMY of HIGHER EDUCATION
(Deemed to be University under Section 3 of the UGC Act, 1956)

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Grokking Machine Learning, Luis G. Serrano, Manning Publications; 1st Edition, 2019. Online resource from Manning Publications available at https://www.manning.com/books/grokking-machine-learning 2. A Course in Machine Learning, Hal Daumé III – Online resource available at http://ciml.info/ 3. An Introduction to Statistical Learning with Applications in R, Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, Springer; 1st Edition, 2013, Corr. 7th printing 2017 Edition. 4. Mathematics for Machine Learning, Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong – Online resource from Cambridge University Press available at https://mml-book.github.io/book/mml-book.pdf.

Name of the Program:	ME in Machine Learning
Course Title:	Applications of Graph Theory
Course Code:MCL 615	**Course Instructor:**
Academic Year: 2020-2021	**Semester:**First Year, Semester 1
No of Credits: 3	**Prerequisites:**Discrete mathematics

Synopsis:	This course introduces basic graph theoretic concepts and some applications in machine learning.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Develop a thorough understanding of fundamental graph theoretic concepts and apply them to understanding practical problems.
CO 2:	Apply appropriate algorithms for solving graph theoretical problems.
CO 3:	Relate a real-life problem to an appropriate graph theoretic setup.
CO 4:	Describe how graph theory can be used for machine learning applications.
CO 5:	Compare and contrast applications of graph theory to small and big data.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2	*	*	*								
CO 3	*	*	*								
CO 4		*	*	*		*				*	
CO 5		*	*	*					*		

Course content and outcomes:

Content	***Competencies***
Unit 1: Graphs; Euler Tours and Hamilton Cycles	
Graphs and their representations - Incidence and adjacency matrices - Vertex degrees - Paths and connection - Cycles - Directed graphs - Subgraphs and supergraphs - The shortest path problem - Forests and trees, Cayley's formula. The traveling salesman problem.	1. Understand basic components of a graph (C2). 2. Understand, compare and contrast incidence and adjacency matrices (C2, C5). 3. Understand the practical applications of the traveling salesman problem (C3).
Unit 2: Flow in Networks;Matchings; Colouring Problems	
Flows and cuts - Max-flow min-cut theorem and its applications.	1. Visualize network flow problems through applications (C3).

Matchings and coverings in bipartite graphs - Perfect matchings - Applications of matchings. Edge colouring& Vertex colouring.	2. Understand matching problems and their practical applications (C3). 3. Understand edge &vertexcolouring and their practical applications (C3).
Unit 3: Random walks and Applications; Spectral Clustering and Applications	
	1. Understand random walks and its practical applications (C3). 2. Model multidimensional data as similarity graph (C4). 3. Understand spectral clustering and its practical applications (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5

Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Introduction to Graph Theory, Richard J. Trudeau, Dover Publications Inc.: 2nd Revised Edition, 1994. 2. Pearls in Graph Theory: A Comprehensive Introduction, Nora Hartsfield and Gerhard Ringel, Dover Publications,2003. 3. Graph Theory, Adrian Bondy, M. Ram Murty, Springer Publications,1st Edition, 2008.

Name of the Program:	ME in Machine Learning
Course Title:	Applications of Graph Theory Lab
Course Code:MCL 615L	**Course Instructor:**
Academic Year: 2020-2021	**Semester:**First Year, Semester 1
No of Credits: 1	**Prerequisites:**MCL 615

Synopsis:	This course provides a practical introduction to understanding, visualizing, and applying basic graph theoretic concepts to practical problems.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Visualize graphs and graph models using Python.
CO 2:	Implement appropriate algorithms for solving graph theoretical problems.
CO 3:	Implement graph theoretic approaches for machine learning applications.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2	*	*	*		*						
CO 3	*	*	*		*						

Course content and outcomes:

Content	***Competencies***
Unit 1: Graphs; Euler Tours and Hamilton Cycles	
Graphs and their representations – Incidence and adjacency matrices – Vertex degrees – Paths and connection - Cycles– Directed graphs – Subgraphs and supergraphs– The shortest path problem – Forests and trees, Cayley's formula. The traveling salesman problem.	1. Visualize graphs using Python (C3). 2. Compute structural properties of graphs such as connectivity using the adjacency matrix (C3).
Unit 2: Flow in Networks;Matchings; Colouring Problems	
Flows and cuts - Max-flow min-cut theorem and its applications. Matchings and coverings in bipartite graphs - Perfect matchings - Applications of matchings.	1. Visualize network flow problems through applications (C3). 2. Implement practical applications of matching, edge &vertexcolouring (C3).

Edge colouring& Vertex colouring.	
Unit 3: Random Walks and Applications; Spectral Clustering and Applications	
	1. Create a random walk and analyse its properties (C4). 2. Model multidimensional data as similarity graph (C4). 3. Apply spectral clustering to practical problems (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Introduction to Graph Theory, Richard J. Trudeau, Dover Publications Inc.: 2nd Revised Edition, 1994. 2. Pearls in Graph Theory: A Comprehensive Introduction, Nora Hartsfield and Gerhard Ringel, DoverPublications,2003. 3. Graph Theory, Adrian Bondy, M. Ram Murty, Springer Publications,1st Edition, 2008.

Name of the Program:	ME in Machine Learning
Course Title:	Principles of Data Visualization
Course Code: BDA 622	**Course Instructor:**
Academic Year:2020-2021	**Semester:**First Year, Semester 1

No of Credits: 3	**Prerequisites:** Programming in Python
Synopsis:	This course provides insight on data visualization, the art and science of turning data into readable graphics; design and create data visualizations based on data available and tasks to be achieved; data extraction, data modelling and data processing; map data attributes to graphical attributes, and strategic visual encoding based on known properties of visual perception.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Extracttransforms and store data from various data sources.
CO 2:	Understand the key techniques and theory used in visualization, including data models, graphical perception and techniques for visual encoding and interaction.
CO 3:	Work with several common data domains and corresponding analysis tasks.
CO 4:	Build and evaluate visualization systems.
CO 5:	Read and discuss research papers from the visualization literature.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*		*		*	*					
CO 2	*	*			*						
CO 3	*	*	*								
CO 4	*		*		*			*			
CO 5	*	*	*	*							

Course content and outcomes:

Content	*Competencies*
Unit 1: Introduction to Web Scraping	
Web scraping models and techniques, Case study: BeautifulSoup, Scrapy, Selenium	1. Understanding various formats of data. (C1) 2. Design programs to dynamically extract data from web. (C4) 3. Design programs to read data from various data sources. (C4)
Unit 2: Data Analysis	

Data structures for analysis: numpy, pandas Data Wrangling: Clean, Transform, Merge, Reshape Data Aggregation and Group Operations Case study: Exploratory analysis of public / scrapped datasets	1. Understand and integrate various data structures for data analysis process (C2). 2. Create various techniques to clean and handle missing data (C4). 3. Design data filtering and transformation techniques (C4).
Unit 3: Data Visualization	
Data Visualization – classification, infographics versus data visualization, visualization for supporting exploratory data analysis, visual art, choosing appropriate visual encodings, rules for visualization - Visualization techniques: time series, statistical distributions, maps - Data visualization for web	1. Describe what is the purpose of Visualization. (C2) 2. Describe several ways of classifying visualization. (C2) 3. Explain what explorative and explanative visualization is. (C2) 4. Differentiate data visualization and visual art. (C2) 5. Create visualization for time series data. (C4) 6. Create visualization for statistical distributions. (C4) 7. Create visualization for maps, Hierarchical data and network data. (C4)

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-

Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. **Website Scraping with Python: Using BeautifulSoup and Scrapy,** Gábor &Hajba, APRESSPublications, 1st Edition, 2018. 2. **Web Scraping with Python: Collecting More Data from the Modern Web**, Ryan Mitchell Shroff, O'Reilly, 2nd Edition, 2018. 3. **Designing Data Visualizations**, Julie Steele and Noah Iliinsky; O'Reilly Media; 1st Edition, 2011. 4. **Python for Data Analysis**, W.McKinney; O'Reilly; 2nd Ed, 2018.

Name of the Program:	ME in Machine Learning
Course Title:	Principles of Data Visualization Lab
Course Code: BDA-622L	**Course Instructor:**

Academic Year: 2020-2021	**Semester:** First year, Semester 1
No of Credits: 1	**Prerequisites:** Programming in Python

Synopsis:	This course provides insight on data visualization, the art and science of turning data into readable graphics; design and create data visualizations based on data available and tasks to be achieved; data extraction, data modelling and data processing; map data attributes to graphical attributes, and strategic visual encoding based on known properties of visual perception.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Scrape data from different data sources.
CO 2:	Clean, analyse, and transform data.
CO 3:	Visualize data using different techniques, tools and charts.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*		*				*	*	
CO 2	*	*	*		*	*		*	*	*	
CO 3	*	*	*	*	*	*		*		*	

Course content and outcomes:

Content	***Competencies***
Unit 1: Data Scrapping	
Web scrapping models Installing and configuring tools to handle different data types.	1. Identify different types of data sources (C2). 2. Design applications to scrap static data (C4). 3. Design applications to extract data from dynamic web pages (C4).
Unit 2: Data Analysis	
Working with packages like numpy, pandas, sklearn Perform exploratory data analysis.	1. Design scripts to clean, handle missing data (C4). 2. Design scripts to apply required transformations to cleaned data (C4).
Unit 3: Data Visualization	

Creating different types of Visualization. Creating different types of charts.	1. Develop applications for exploratory data visualization (C4). 2. Develop scripts to create static visualization using various visual encodings (C4). 3. Create dynamic visualization for web (C4).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3
Sessional Examination 1	*		

Sessional Examination 2		*	*
Assignment/Presentation	*	*	*
End Semester Examination	*	*	*
Laboratory Examination	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. **Website Scraping with Python: Using BeautifulSoup and Scrapy,** Gábor &Hajba, APRESSPublications, 1st Edition, 2018. 2. **Web Scraping with Python: Collecting More Data from the Modern Web**, Ryan Mitchell Shroff, O'Reilly, 2nd Edition, 2018. 3. **Designing Data Visualizations**, Julie Steele and Noah Iliinsky; O'Reilly Media; 1st Edition, 2011. 4. **Python for Data Analysis**, Wes McKinney; Shroff; O'Reilly; 2nd Edition, 2018.

Name of the Program:	ME in Machine Learning
Course Title:	Architecture of Big Data Systems
Course Code: BDA 623	**Course Instructor:**
Academic Year:2020-2021	**Semester:** First Year, Semester 1

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No of Credits: 3	**Prerequisites:** Programming in Python, Java
Synopsis:	This Course provides insight on concept of big data characteristics, batch and lambda architecture; basic file systems in Big Data; concepts of Hadoop framework, Spark framework and their internals; Map-reduce programming, Spark programming; different layers with use cases demonstrations.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Examine the type of data in big data.
CO 2:	To design applications based with Hadoop framework.
CO 3:	To design applications based with spark architecture.
CO 4:	To build applications based on the Big Data Architecture platforms and analyse the results based on the outcome of the applications used.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*			*					
CO 2	*	*	*		*		*			*	
CO 3	*	*	*		*		*			*	
CO 4	*	*	*		*	*	*			*	

Course content and outcomes:

Content	***Competencies***
Unit 1: Classifying Big Data Characteristics	
Analysis type - real time or batched for later analysis. Processing methodology - predictive, analytical, ad-hoc query, and reporting. Data frequency and size On demand, as with social media data Continuous feed, real-time - weather data, transactional data Time series - time-based data	1. Identify different types of Data 2. Identify processing methodology

Data type - transactional, historical, master data and metadata. Content formats - structured, unstructured, semi-structured Data sources - Web and social media, humans, machines, transaction data and biometric data.	
Unit 2: Big Data Processing - the Lambda architecture	
Append-only, immutable data Batch layer Serving layer Speed layer Case study: Druid - A Real-time Analytical Data Store	1. Understand Lambda architecture to handle Big Data (C2). 2. Understand different layers in Lambda Architecture (C2).
Unit 3: Batch Layer, Serving Layer and Speed Layer	
Choosing a storage solution for the batch layer: Distributed file systems, Vertical partitioning. MapReduce: a paradigm for Big Data computing. Performance metrics for the serving layer Requirements for a serving layer database Computing real time views Storing real time views Challenges of incremental computation Asynchronous versus synchronous updates	1. Develop applications to store data in HDFS (C4). 2. Develop applications for batch processing using Map Reduce technique (C4). 3. Understand the need of serving layer (C2). 4. Design application to store data for processing in serving layer (C4). 5. Understand the need of Speed layer for data processing (C2).
Unit 4:Spark: Alternatives to MapReduce	
Spark Architecture Spark Session	1. Understand Spark Architecture for data processing (C2).

DataFrame Transformations and Actions Spark SQL Resilient Distributed Datasets (RDDs)	2. Design applications using DataFrames and RDDs (C4).
Unit 5: Stream Processing using Spark	
Advantages and challenges of stream processing Stream Processing Design Points Streaming APIs Structured Stream Processing	1. Understand different stream processing techniques (C2). 2. Design applications for handling real time data using Structured Streaming (C4).
Unit 6: Machine Learning using Spark.	
High level M-Lib concepts M-Lib in Action	1. Understand different libraries and packages for machine learning in Spark (C2). 2. Design machine learning model using Spark (C4).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination

Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4
Sessional Examination 1	*	*		
Sessional Examination 2		*	*	
Assignment/Presentation				*
End Semester Examination	*	*	*	*
Laboratory examination	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Big Data: Principles and best practices of scalable real-time data systems - Nathan Marz and James Warren. Manning Publisher. 2. Hadoop: The Definitive Guide: Storage and Analysis at Internet Scale – Tom White, O'Reilly Publication 4th Edition. 3. Spark: The Definitive Guide: Big Data Processing Made Simple – Bill Chambers, Matei Zaharia, O'Reilly Publication 1st Edition. 4. http://static.druid.io/docs/druid.pdf, http://druid.io/docs/0.8.0/design/design.html 5. Big data architecture and patterns - IBM developer Works. http://www.ibm.com/developerworks/library/bd-archpatterns1/ 6. Big Data and Analytics -IBM developer Works. http://www.ibm.com/developerworks/analytics/ 7. http://lambda-architecture.net/ 8. Apache HBase - http://hbase.apache.org/ 9. Apache Spark Streaming - https://spark.apache.org/streaming/ 10. MapReduce library - https://github.com/twitter/summingbird

Name of the Program:	ME in Machine Learning
Course Title:	Architecture of Big Data Systems Lab
Course Code: BDA 623L	**Course Instructor:**
Academic Year:2020-2021	**Semester:**First year, Semester 1

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No of Credits: 1	**Prerequisites:** Programming in Python, Java
Synopsis:	This Course provides insight on concept of big data characteristics, batch and lambda architecture; basic file systems in Big Data; concepts of Hadoop framework, Spark framework and their internals; Map-reduce programming, Spark programming; different layers with use cases demonstrations.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Install and develop applications using Hadoop and its ecosystems.
CO 2:	Build applications using Spark framework.
CO 3:	Build Machine Learning models using Spark.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*		*	*			*	*	
CO 2	*	*	*		*	*			*	*	
CO 3	*	*	*		*	*			*	*	

Course content and outcomes:

Content	*Competencies*
Unit 1: Hadoop Ecosystem	
Installation and configuring Hadoop ecosystem	1. Practice applications in HDFS and YARN. (C3) 2. Practice applications using Sqoop, Hive, PIG. (C3) 3. Compute programs using MapReduce. (C3)
Unit 2: Spark Framework	
Spark tool chain – RDD, DataFrame, SQL and Streaming	1. Develop applications using Spark DataFrame and SQL (C4). 2. Design real time applications using Spark Streaming (C4).
Unit 3: Machine Learning using Spark	

MLIB	1. Compute machine learning models using Spark. (C3)

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3
Sessional Examination 1	*		
Sessional Examination 2		*	*
Assignment/Presentation	*	*	*
End Semester Examination	*	*	*

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Laboratory Examination	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Big Data: Principles and best practices of scalable real-time data systems - Nathan Marz and James Warren. Manning Publisher. 2. Hadoop: The Definitive Guide: Storage and Analysis at Internet Scale – Tom White, O’Reilly Publication 4th Edition. 3. Spark: The Definitive Guide: Big Data Processing Made Simple – Bill Chambers, Matei Zaharia, O’Reilly Publication 1st Edition.

Name of the Program:	ME in Machine Learning
Course Title:	Mini Project - 1
Course Code: MCL 695	**Course Instructor:**
Academic Year:2020 -2021	**Semester:**First Year, Semester1
No of Credits: 4	**Prerequisites:** Programming in Python / R

Synopsis:	Students are expected to select a problem in the area of their interest and the area of their specialization that would require an implementation in hardware / software or both in a semester
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1	Apply the objectives of the project work and provide an adequate background with a detailed literature survey
CO 2	Breakdown the project into sub blocks with sufficient details to allow the work to be reproduced by an independent researcher
CO 3	Compose hardware/software design, algorithms, flowchart, methodology, and block diagram
CO 4	Evaluate the results
CO 5	Summarize the work carried out

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1				*							
CO 2					*			*			
CO 3							*			*	
CO 4						*					*
CO 5							*				

Course content and outcomes:

Content	***Competencies***
Phase 1	
Problem identification, synopsis submission, status submission, mid evaluation.	At the end of the topic student should be able to: 1. Identify the problem/specification (C1) 2. Discuss the project (C2) 3. Prepare the outline (C3) 4. Describe the status of the project (C2) 5. Prepare a mid-term project presentation report (C3)

	6. Prepare and present mid-term project presentation slides (C3, C5) 7. Develop project implementation in hardware/software or both in chosen platform (C5)
Phase 2	
Status submission, final evaluation.	1. Prepare the progress report (C3) 2. Prepare the final project presentation report (C3) 3. Prepare and present final project presentation slides (C3, C5) 4. Modify and Develop implementation in hardware/software or both in chosen platform (C3, C5) 5. Justify the methods used and obtained results (C6)

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	-	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	48	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	-	-
Clinic	-	-
Practical	-	-
Revision	-	-
Assessment	03	-
TOTAL	**51**	**09**

Assessment Methods:						
Formative:				**Summative:**		
Project Problem Selection				Mid-Term Presentation		
Synopsys review				Second status review		
First status review				Demo & Final Presentation		
Mapping of assessment with Cos						
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CO 5
Mid Presentation		*	*			
Presentation		*	*	*	*	*
Feedback Process	• End-Semester Feedback					
Reference Material	Particular to the chosen project					

Name of the Program:	ME in Machine Learning
Course Title:	Seminar - 1
Course Code: MCL 697	**Course Instructor:**
Academic Year:2020 -2021	**Semester:**First Year, Semester 1
No of Credits: 1	**Prerequisites:** Communication Skill

Synopsis:	1. To select, search and learn technical literature. 2. To Identify a current and relevant research topic. 3. To prepare a topic and deliver a presentation. 4. To develop the skill to author a technical report. 5. Develop ability to work in groups to review and modify technical content.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1	Show competence in identifying relevant information, defining and explaining topics under discussion.
CO 2	Show competence in working with a methodology, structuring their oral work, and synthesizing information.
CO 3	Use appropriate registers and vocabulary, and will demonstrate command of voice modulation, voice projection, and pacing.
CO 4	Demonstrate that they have paid close attention to what others say and can respond constructively.
CO 5	Develop persuasive speech, present information in a compelling, well-structured, and logical sequence, respond respectfully to opposing ideas, show depth of knowledge of complex subjects, and develop their ability to synthesize, evaluate and reflect on information.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*							*	*		*
CO 2	*							*	*		*
CO 3	*							*	*		*
CO 4	*							*	*		*
CO5	*							*	*		*

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	-	-

Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	14	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	-	-
Clinic	-	-
Practical	-	-
Revision	-	-
Assessment	-	-
TOTAL	**14**	**-**

Assessment Methods:	
Formative:	**Summative:**
Seminar Topic Selection	
Synopsys review	
PPT Review	

Mapping of assessment with Cos					
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Presentation	*	*	*	*	*

Feedback Process	• End-Semester Feedback
Reference Material	Particular to the chosen Seminar

Name of the Program:	ME in Machine Learning
Course Title:	Advanced Applications of Probability and Statistics
Course Code:MCL 602	**Course Instructor:**
Academic Year: 2020-2021	**Semester:**First Year, Semester 2
No of Credits: 3	**Prerequisites:**MCL 601, 603

Synopsis:	This course introduces advanced applications of probability and statistics for multivariate and time series data.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Compute and interpret descriptive statistics for multivariate data
CO 2:	Apply linear and logistic regression models for practical problems and assess model performance
CO 3:	Interpret the output of principal component analysis (PCA) applied to multivariate data for dimension reduction
CO 4:	Identify multivariate data with mixed data type features and cluster using an appropriate technique
CO 5:	Understand the basics of time series modelling and apply to real-life problems

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*		*								
CO 2	*	*	*	*							
CO 3	*	*	*	*				*			
CO 4		*	*	*	*	*					
CO 5	*	*	*								

Course content and outcomes:

Content	***Competencies***
Unit 1: Multivariate Distributions	
Mean vector, covariance and correlation – population vs. sample - The multivariate Gaussian – joint-, marginal-, and conditional distributions, Mahalanobis distance and outliers - Properties of the multivariate Gaussian - Parameter estimation: maximum likelihood estimation (MLE) and maximum aposteriori estimation (MAP).	1. Understand the organisation of multivariate data (C2). 2. Relate multivariate population and sample parameters (C4). 3. Understand and apply multivariate Gaussian modelling to practical problems (C2, C3). 4. Compare parameter estimation using different probabilistic approaches (C4).

Unit 2: Linear and Logistic Regression	
Simple linear regression – regression model, estimating and interpreting coefficients, accuracy of coefficient estimates and model, ANOVA, R2 statistic - Multiple linear regression – estimating coefficients, qualitative predictors, interaction effects, potential problems - Logistic regression – binary and multinomial logistic regression models, estimating and interpreting coefficients, assessing model calibration and discrimination, area under the ROC curve.	1. Model a linear relationship between input and output variables and assess model performance (C5). 2. Use different performance metrics to conclude what is a good linear fit to the data (C6). 3. Interpret model coefficients and investigate the effect of input variables on output through sensitivity analysis (C6). 4. Apply logistic regression modelling for binary and multiclass classification and assess model performance (C6).
Unit 3: Principal Component Analysis; Cluster Analysis	
Geometric intuition of principal components - Maximum variance perspective – algebraic setup, eigenvectors and eigenvalues of sample correlation matrix - Interpretation and application of principal components for dimension reduction. Dissimilarity measures for mixed data types - Partition around medoids (PAM) vs. K-means algorithms - Selecting the number of clusters.	1. Understand the mathematical foundation of principal component analysis (PCA) (C2). 2. Perform and interpret the output of PCA applied to multivariate data for dimension reduction (C6). 3. Assess when PCA is applicable for clustering multivariate data (C6). 4. Compare and contrast methods for clustering multivariate data with mixed data types (C6).
Unit 4: Bootstrapping; Time Series Analysis	

Time series concepts: stationarity, trend, seasonality, autocorrelation - Autoregressive moving average (ARMA) models - Resampling, smoothing, windowing, and rolling average - First and second order differencing - Validating time series predictions.	1. Understand the basic principles of bootstrapping as an experimental method to estimate the sampling distributions of a statistic (C2). 2. Understand the basic mathematical principles of time series modelling (C2). 3. Apply time series modelling to practical problems (C3). 4. Interpret the results of times series model predictions (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	

Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. An Introduction to Statistical Learning with Applications in R, Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, Springer; 1st Edition, 2013, Corr. 7th printing 2017 Edition. 2. An Introduction to Applied Multivariate Analysis with R, Brian Everitt and Torsten Hothorn– Springer Publications,1st Edition, 2011. 3. Machine Learning - A Probabilistic Perspective, Kevin P. Murphy, The MIT Press; 1st Edition, 2012. 4. Mathematics for Machine Learning, Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong, Cambridge University Press, 2020. – Online resource from Cambridge University Press available at https://mml-book.github.io/book/mml-book.pdf

Name of the Program:	ME in Machine Learning
Course Title:	Advanced Applications of Probability and Statistics Lab
Course Code:MCL 602L	**Course Instructor:**

Academic Year:2020-2021	**Semester:**First Year, Semester 2
No of Credits: 1	**Prerequisites:**MCL 602

Synopsis:	This course introduces advanced applications of probability and statistics for analysing multivariate and time series data using the R programming language.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Compute and interpret descriptive statistics for multivariate data
CO 2:	Build and assess linear and logistic regression models for practical problems
CO 3:	Perform principal component analysis (PCA) for dimension reduction in multivariate data
CO 4:	Cluster multivariate data with mixed data types
CO 5:	Apply time series modelling to real-life problems

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*		*						
CO 2		*	*	*	*			*			
CO 3		*	*	*	*			*			
CO 4		*	*	*	*	*		*			
CO 5	*	*	*								

Course content and outcomes:

Content	***Competencies***
Unit 1: Multivariate Distributions	
Mean vector, covariance and correlation – population vs. sample - The multivariate Gaussian – joint-, marginal-, and conditional distributions, Mahalanobis distance and outliers - Properties of the multivariate Gaussian - Parameter estimation: maximum likelihood estimation (MLE) and	1. Compute descriptive statistics of multivariate data (C2). 2. Perform exploratory data analysis of multivariate data (C4). 3. Identify outliers in multivariate data (C3). 4. Visualise and understand the properties of multivariate Gaussian data (C3).

maximum aposteriori estimation (MAP).	
Unit 2: Linear and Logistic Regression	
Simple linear regression – regression model, estimating and interpreting coefficients, accuracy of coefficient estimates and model, ANOVA, R2 statistic - Multiple linear regression – estimating coefficients, qualitative predictors, interaction effects, potential problems - Logistic regression – binary and multinomial logistic regression models, estimating and interpreting coefficients, assessing model calibration and discrimination, area under the ROC curve.	1. Use in-built functions in R to build linear models for practical problem (C3). 2. Compute different performance metrics to assess model performance (C6). 3. Interpret model coefficients and investigate the effect of input variables on output through sensitivity analysis (C6). 4. Use in-built functions in R to build logistic regression models for practical binary classification problems and assess model performance (C6).
Unit 3: Principal Component Analysis; Cluster Analysis	
Geometric intuition of principal components - Maximum variance perspective – algebraic setup, eigenvectors and eigenvalues of sample correlation matrix - Interpretation and application of principal components for dimension reduction. Dissimilarity measures for mixed data types - Partition around medoids (PAM) vs. K-means algorithms - Selecting the number of clusters.	1. Visualise the geometric interpretation of principal component analysis (PCA) (C3). 2. Use in-built functions in R to perform PCA on multivariate data (C3). 3. Compare and contrast PCA for variance maximization vs. clustering of multivariate data (C6). 4. Cluster multivariate data with mixed data types using in-built functions in R (C3).
Unit 4: Bootstrapping; Time Series Analysis	
Time series concepts: stationarity, trend, seasonality, autocorrelation - Autoregressive moving average	1. Apply bootstrapping on a practical data set and assess performance (C3).

(ARMA) models - Resampling, smoothing, windowing, and rolling average - First and second order differencing - Validating time series predictions.	2. Understand and apply in-built functions in R for time series modelling (C3). 3. Apply time series modelling to practical problems (C3). 4. Interpret the results of times series model predictions (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			

Sessional Examination 2			*	*	*
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. An Introduction to Statistical Learning with Applications in R, Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, Springer; 1st Edition, 2013, Corr. 7th printing 2017 Edition. 2. An Introduction to Applied Multivariate Analysis with R, Brian Everitt and Torsten Hothorn– Springer Publications,1st Edition, 2011. 3. Machine Learning - A Probabilistic Perspective, Kevin P. Murphy, The MIT Press; 1st Edition, 2012. 4. Mathematics for Machine Learning, Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong, Cambridge University Press, 2020. – Online resource from Cambridge University Press available at https://mml-book.github.io/book/mml-book.pdf

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Course Title:	Machine Learning Principles & Applications
Course Code: MCL 604	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 3	**Prerequisites:** MCL 601, 603, 605

Synopsis:	This course provides an advanced treatment of machine learning algorithms and the underlying mathematics essential for careful selection and analysis of algorithms for practical applications.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Develop practical experience with state-of-the-art machine learning tools and libraries.
CO 2:	Differentiate between discriminative and generative algorithms for supervised machine learning.
CO 3:	Evaluate machine learning algorithms for accuracy and performance.
CO 4:	Devise techniques for dealing with practical difficulties in applying machine learning techniques to real-life problems.
CO 5:	Develop low dimensional models of application problems with mixed data type features.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*		*		*						
CO 2	*	*		*							
CO 3	*	*	*	*	*						
CO 4		*	*	*	*	*		*			
CO 5		*	*	*		*					

Course content and outcomes:

Content	*Competencies*
Unit 1: Kernel Methods; Linear Regression	
Kernels as feature maps - Kernel functions: types, hyperparameters - Kernel matrix: interpretation and properties - Kernel (nonlinear) SVM. Least mean squares (LMS) algorithm: cost function - Gradient descent algorithm: learning rate, batch and	1. Understand the relationship between kernel functions and feature mapping (C2). 2. Understand how to develop nonlinear models from linear ones using kernels (C2, C5). 3. Construct the cost function for least mean squares algorithm and apply gradient descent (C5).

stochastic gradient approaches - Probabilistic interpretation of linear regression: MLE and MAP estimates.	4. Compare probabilistic interpretation of linear regression with linear algebra-based interpretation (C6).
Unit 2: Generative Learning Algorithms; Regularization, Model Selection, & Evaluation	
Gaussian discriminant analysis (GDA) - Naive Bayes algorithm: MLE estimates, Laplace smoothing. Grid search for best hyperparameters - Cross validation: types and practical approaches - Featureselection: forward/backward search, wrapper model & filter feature selection - Metrics for evaluating supervised & unsupervised machine learning algorithms.	1. Model data flexibly by specifying a proper probabilistic model (C4). 2. Develop an optimization view of machine learning through MLE estimates (C5). 3. Understand how to efficiently identifyoptimal values of hyperparameters using grid search (C2, C3). 4. Choose appropriate feature engineering approaches and quantitatively compare machine learning algorithms (C6).
Unit 3:Imbalanced Data; Expectation Maximization; Dimension Reduction; Independent Component Analysis	
Modifying the training data: over- and under-sampling - Modifying the loss function. Clustering with a mixture of Gaussians - Expectation maximization (EM) framework. Factor analysis (FA) - Generalized low rank models (GLRM). Independent Component Analysis (ICA)	1. Compare different approaches for dealing with missing data (C6). 2. Relate the EM framework for clustering with K-means clustering. 3. Construct and interpret low dimensional models of data (C5). 4. Develop models for analysingmixed datatype data (C5).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. A Course in Machine Learning, Hal Daumé III – Online resource available at http://ciml.info/ 2. Machine Learning: A Probabilistic Perspective, Kevin Murphy, MIT Press,2017.

	3. An Introduction to Statistical Learning with Applications in R, Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, Springer Publications, 2017. 4. Lecture slides of Prof. Andrew Ng – Stanford University – Available online at http://cs229.stanford.edu/syllabus.html 5. Mathematics for Machine Learning, Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong – Online resource from Cambridge University Press available at https://mml-book.github.io/book/mml-book.pdf 6. Pattern Recognition and Machine Learning, Christopher Bishop, Springer Publications, 2017.

Name of the Program:	ME in Machine Learning
Course Title:	Machine Learning Principles and Applications Lab
Course Code:MCL 604L	**Course Instructor:**

Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 1	**Prerequisites:** MCL 604

Synopsis:	This course provides a practical introduction to advanced machine learning algorithms with an emphasis on careful analysis and selection of algorithms for practical problems.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Practically apply state of the art machine learning tools and libraries.
CO 2:	Implement and compare discriminative and generative supervised machine learning algorithms for practical problems.
CO 3:	Evaluate machine learning algorithms for accuracy and performance for practical problems.
CO 4:	Implement different strategies for selecting features and dealing with missing data.
CO 5:	Implement machine learning models for real-life data with mixed datatype features.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1			*		*						
CO 2		*	*	*	*						
CO 3		*	*	*	*			*			
CO 4		*	*	*	*						
CO 5		*	*	*	*	*				*	

Course content and outcomes:

Content	***Competencies***
Unit 1: Kernel Methods; Linear Regression	
Kernels as feature maps - Kernel functions: types, hyperparameters - Kernel matrix: interpretation and properties - Kernel (nonlinear) SVM.	1. Implement and compare different kernels for feature mapping (C4). 2. Implement kernel SVM and investigate the effects of model parameters through visualization (C4).

Least mean squares (LMS) algorithm: cost function - Gradient descent algorithm: learning rate, batch and stochastic gradient approaches - Probabilistic interpretation of linear regression: MLE and MAP estimates.	3. Implement gradient descent for least mean squares algorithm and investigate the effects of hyperparameters on performance (C4). 4. Compare linear regression applied to practical problems with and without regularization (C4).
Unit 2: Generative Learning Algorithms; Regularization, Model Selection, & Evaluation	
Gaussian discriminant analysis (GDA) - Naive Bayes algorithm: MLE estimates, Laplace smoothing. Grid search for best hyperparameters - Cross validation: types and practical approaches - Featureselection: forward/backward search, wrapper model & filter feature selection - Metrics for evaluating supervised & unsupervised machine learning algorithms.	1. Implement probabilistic models of data (C4). 2. Perform grid search to identify best model hyperparameters (C3). 3. Perform feature engineering for real-life problems (C3). 4. Evaluate machine learning algorithms using well established performance metrics (C3).
Unit 3:Imbalanced Data; Expectation Maximization; Dimension Reduction; Independent Component Analysis	
Modifying the training data: over- and under-sampling - Modifying the loss function. Clustering with a mixture of Gaussians - Expectation maximization (EM)framework. Factor analysis (FA) - Generalized low rank models (GLRM).	1. Implement and compare different approaches for dealing with missing data in real-life problems (C6). 2. Implement and interpret low dimensional models of data (C4). 3. Implement models for analysing mixed datatype data (C4).

Independent Component Analysis (ICA)	4. Compare and contrast different techniques for dimension reduction and their practical implications (C6).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	*
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. A Course in Machine Learning, Hal Daumé III – Online resource available at http://ciml.info/ 2. Machine Learning: A Probabilistic Perspective, Kevin Murphy, MIT Press,2017. 3. An Introduction to Statistical Learning with Applications in R, Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani, Springer Publications, 2017. 4. Lecture slides of Prof. Andrew Ng – Stanford University – Available online at http://cs229.stanford.edu/syllabus.html 5. Mathematics for Machine Learning, Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong – Online resource from Cambridge University Press available at https://mml-book.github.io/book/mml-book.pdf 6. Pattern Recognition and Machine Learning, Christopher Bishop, Springer Publications, 2017.

Name of the Program:	ME in Machine Learning

Course Title:	Deep Learning
Course Code: MCL 606	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 3	**Prerequisites:** MCL 601, 603, 605

Synopsis:	This course provides a through computational foundation to the principles of deep learning and its applications.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Gain a solid understanding of the mathematical basis of neural networks.
CO 2:	Develop practical experience with state-of-the-art deep learning tools and libraries.
CO 3:	Build and analyse deep learning models for application problems.
CO 4:	Devise techniques for improving the way neural networks learn.
CO 5:	Develop skills to choose an appropriate deep learning model.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*									
CO 2	*	*	*		*						
CO 3		*	*	*	*						
CO 4		*	*	*	*			*			
CO 5		*	*	*	*	*			*		

Course content and outcomes:

Content	***Competencies***
Unit 1: Introduction to Deep Learning; Matrix Calculus; Logistic Regression	
Sigmoid neurons - The architecture of neural networks. Derivatives in one dimension - Derivative in multiple dimensions: gradient and Jacobian matrices - Rules of matrix calculus: product and chain rules -Optimizing using the gradient descent method– intuition and principle.	5. Understand the basic architecture of a sigmoid neuron (C2). 6. Reconstruct derivatives of multivariable functions using ideas from single variable calculus and linear algebra (C5). 7. Develop intuition behind the gradient descent method (C5). 8. Formulate the cost function for binary classification using logistic regression using vectorized approach (C5).

Binary classification using logistic regression: cost function, gradient descent, and vectorization.	
Unit 2:Shallow Neural Network	
One hidden layer neural network: architecture and notation - The role of activation functions and their derivatives - Forward propagation using matrix-based approach - Cost/loss function: intuition and setup - Gradient descent: backpropagation intuition and vectorized setup using matrix-based approach - Random initialization of network parameters.	5. Develop intuition for nonlinear activation functions (C5). 6. Formulate backpropagation using matrix-based approach (C5). 7. Develop intuition for and formulate loss functions in deep learning (C5). 8. Understand the importance of random initialization of network parameters (C2).
Unit 3:Deep Neural Network; Improving the Way neural Networks Learn	
Deep L-layer neural network: architecture, notation, and building blocks - Forward and backward propagation in a deep neural network using matrix-based approach - The importance of deep representations - Parameters vs. hyperparameters. The cross-entropy cost function - The learning slowdown problem - Overfitting and regularization: L1/L2, dropout - Weight initialization.	1. Extend ideas from shallow neural network to a deep neural network (C2). 2. Formulate forward and backward propagation for a deep neural network using matrix-based approach (C5). 3. Compare and contrast parameters and hyperparameters (C6). 4. Gain an intuitive understanding of overfitting and the use of regularization using different approaches (C2).
Unit 4:Hyperparameter Tuning; Recurrent Neural Networks	
Random initialization using appropriate scales - Batch normalization.	5. Understand how to tune hyperparameters (C2). 6. Intuitively understand the architecture of a recurrent neural network (C2).

Recurrent neural network: architecture and notation - Forward and backward propagation through time - Different types of recurrent neural networks and their applications.	7. Compare and contrast feed forward and recurrent neural networks (C6). 8. Understand how to perform forward and backward propagation for recurrent neural networks.

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback

	• End-Semester Feedback
Reference Material	7. Neural Networks and Deep Learning, Michael Nielsen – Determination Press – Available online at http://neuralnetworksanddeeplearning.com/index.html 8. Lecture slides of Prof. Andrew Ng – Stanford University – Available online at https://cs230.stanford.edu/syllabus/ 9. Deep Learning, Ian Goodfellow, Yoshua Bengio, and Aaron Courville – MIT Press – Available online at http://www.deeplearningbook.org/

Name of the Program:	ME in Machine Learning
Course Title:	Deep Learning Lab

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(Deemed to be University under Section 3 of the UGC Act, 1956)

Course Code: MCL 606L	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 1	**Prerequisites:** MCL 606

Synopsis:	This course provides a practical foundation to implementing deep learning algorithms for real-life problems using state of the art software.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Gain a deeper understanding of matrix calculus through Python programming.
CO 2:	Develop practical experience with state-of-the-art deep learning tools and libraries.
CO 3:	Implement deep learning models for application problems.
CO 4:	Implement techniques for improving the way neural networks learn.
CO 5:	Numerically analyse deep learning models and select the best model.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*				*						
CO 2		*	*		*						
CO 3		*	*	*	*						
CO 4		*	*	*	*						
CO 5		*	*	*	*	*		*			

Course content and outcomes:

Content	*Competencies*
Unit 1: Introduction to Deep Learning; Matrix Calculus; Logistic Regression	
Sigmoid neurons - The architecture of neural networks. Derivatives in one dimension - Derivative in multiple dimensions: gradient and Jacobian matrices - Rules of matrix calculus: product and chain rules -Optimizing using the gradient descent method– intuition and principle.	1. Implement a sigmoid neuron from scratch (C3). 2. Implement forward and backward propagation for a sigmoid neuron (C3). 3. Implement gradient descent for a sigmoid neuron (C3). 4. Implement cost function for binary classification using logistic regression using vectorized approach (C3).

Binary classification using logistic regression: cost function, gradient descent, and vectorization.	
Unit 2:Shallow Neural Network	
One hidden layer neural network: architecture and notation - The role of activation functions and their derivatives - Forward propagation using matrix-based approach - Cost/loss function: intuition and setup - Gradient descent: backpropagation intuition and vectorized setup using matrix-based approach - Random initialization of network parameters.	1. Visualize different nonlinear activation functions (C3). 2. Implement forward and backward propagation for a shallow neural network using matrix-based approach (C3). 3. Implement gradient descent method for a shallow neural network (C3). 4. Numerically investigate the effect of random initialization of network parameters (C4).
Unit 3:Deep Neural Network; Improving the Way neural Networks Learn	
Deep L-layer neural network: architecture, notation, and building blocks - Forward and backward propagation in a deep neural network using matrix-based approach - The importance of deep representations - Parameters vs. hyperparameters. The cross-entropy cost function - The learning slowdown problem - Overfitting and regularization: L1/L2, dropout - Weight initialization.	1. Visualise architecture of a deep neural network (C3). 2. Implement forward and backward propagation for a deep neural network using matrix-based approach (C3). 3. Implement deep neural networks using in-built libraries for real-life problems (C4). 4. Implement different regularization approaches and compare their advantages and disadvantages (C6).
Unit 4:Hyperparameter Tuning; Recurrent Neural Networks	
Random initialization using appropriate scales - Batch normalization.	1. Fine tune hyperparameters (C3). 2. Numerically investigate the effect of random initialization in deep neural networks (C4).

Recurrent neural network: architecture and notation - Forward and backward propagation through time - Different types of recurrent neural networks and their applications.	3. Visualise the architecture of a recurrent neural network (C3). 4. Implement recurrent neural network models for real-life problems.

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	*

Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Neural Networks and Deep Learning, Michael Nielsen – Determination Press – Available online at http://neuralnetworksanddeeplearning.com/index.html 2. Lecture slides of Prof. Andrew Ng – Stanford University – Available online at https://cs230.stanford.edu/syllabus/ 3. Deep Learning, Ian Goodfellow, Yoshua Bengio, and Aaron Courville – MIT Press – Available online at http://www.deeplearningbook.org/

Name of the Program:	ME in Machine Learning
Course Title:	Reinforcement Learning

Course Code: MCL 608	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 3	**Prerequisites:** MCL 601, 603

Synopsis:	This course provides a thorough computational foundation to the principles of reinforcement learning and its applications.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Define the key features of reinforcement learning that distinguishes it from AI and non-interactive machine learning.
CO 2:	Understand how ideas such as temporal difference learning and dynamic programming fit in the framework of learning from interaction to achieve goals.
CO 3:	Decide if an application problem can be formulated as a reinforcement learning problem and choose an appropriate algorithm.
CO 4:	Understand and implement commonly used reinforcement learning algorithms.
CO 5:	Analyse algorithms for reinforcement learning.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2	*	*									
CO 3		*	*	*							
CO 4		*	*	*	*						
CO 5		*	*	*	*	*					

Course content and outcomes:

Content	*Competencies*
Unit 1: Introduction to the Reinforcement Learning Problem; Reinforcement Learning Framework; Dynamic Programming	
Examples and elements of reinforcement learning - Limitations and scope of reinforcement learning - History of reinforcement learning. n-Armed bandit problem: action-value methods - Finite Markov decision process: the agent–environment	1. Gain an intuitive understanding of reinforcement learning, related terminology, and contrast it with other machine learning algorithms such as deep learning (C2, C6). 2. Demonstrate the exploration versus exploitation dilemma using the n-Armed bandit problem (C3, C4).

interface, goals and rewards, returns, Markov decision processes, value functions, and optimal value functions.	3. Gain an intuitive understanding of a Markov decision process (C2). 4. Formulate a reinforcement learning task as a Markov decision process (C5).
Unit 2:Model Free Reinforcement Learning	
Generalized policy iteration - Importance of exploration - Monte Carlo control - Temporal difference methods for control.	1. Understand policy iteration using an iterative policy evaluation approach (C2, C4). 2. Understand how policy evaluation and policy improvement processes interact (C2, C4). 3. Solve reinforcement learning tasks using Monte Carlo methods (C3, C4). 4. Combine dynamic programming and Monte Carlo ideas to formulate temporal difference methods for solving reinforcement learning tasks (C5).
Unit 3:Approximate Solution Methods; Policy Based Methods	
Value prediction with function approximation - Gradient-descent methods - Linear methods - Control with function approximation. Policy gradient - Actor–critic methods - Policy-based vs. value-based methods - Integrating supervised & reinforcement learning.	1. Formulate function approximation methods for value prediction (C5). 2. Understand the assumptions of linear value function approximators (C2). 3. Compare and contrast policy-based and value-based methods for reinforcement learning (C6). 4. Explore integration of supervised and reinforcement learning (C5).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02

Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process

- Mid-Semester feedback
- End-Semester Feedback

Reference Material

1. Reinforcement Learning: An Introduction, Richard S. Sutton and Andrew G. Barto, MIT Press, 2nd Edition – Available online at https://web.stanford.edu/class/psych209/Readings/SuttonBartoIPRLBook2ndEd.pdf
2. Lecture slides of Prof. Emma Brunskill – Stanford University – Available online at http://web.stanford.edu/class/cs234/schedule.html
3. Generative Deep Learning: Teaching Machines to Paint, Write, Compose, and Play, David Foster – O'Reilly, 1st Edition, 2019.
4. Reinforcement Learning and Optimal Control, Dimitri Bertsekas, Athena Scientific; 1st Edition, 2019.

Name of the Program:	ME in Machine Learning
Course Title:	Reinforcement Learning Lab

Course Code: MCL 608L	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 1	**Prerequisites:** MCL 608

Synopsis:	This course provides a practical foundation for implementing reinforcement learning algorithms for real-life problems using state of the art software.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Understand the trade-off between exploration vs. exploitation approaches in solving reinforcement learning tasks.
CO 2:	Use dynamic programming approach to solve reinforcement learning tasks.
CO 3:	Model real-life problems using Markov decision processes.
CO 4:	Compare and contrast several methods for solving reinforcement learning tasks.
CO 5:	Computationally analyse algorithms for reinforcement learning.

Mapping of COs to Pos

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*		*						
CO 2	*	*	*		*						
CO 3	*	*	*	*	*						
CO 4	*	*	*	*	*						
CO 5				*	*						

Course content and outcomes:

Content	***Competencies***
Unit 1: Introduction to the Reinforcement Learning Problem; Reinforcement Learning Framework; Dynamic Programming	
Examples and elements of reinforcement learning - Limitations and scope of reinforcement learning - History of reinforcement learning. n-Armed bandit problem: action-value methods - Finite Markov decision	1. Implement building blocks for solving a reinforcement learning task (C3). 2. Solve an n-Armed bandit problem using different exploration strategies (C3). 3. Implement Markov decision process models (C3).

process: the agent–environment interface, goals and rewards, returns, Markov decision processes, value functions, and optimal value functions.	
Unit 2:Model Free Reinforcement Learning	
Generalized policy iteration - Importance of exploration - Monte Carlo control - Temporal difference methods for control.	1. Implement iterative policy evaluation (C3). 2. Implement Monte Carlo methods for solving reinforcement learning tasks (C3). 3. Implement temporal difference methods for solving reinforcement learning tasks (C3).
Unit 3:Approximate Solution Methods; Policy Based Methods	
Value prediction with function approximation - Gradient-descent methods - Linear methods - Control with function approximation. Policy gradient - Actor–critic methods - Policy-based vs. value-based methods - Integrating supervised & reinforcement learning.	1. Implement function approximation methods for value prediction (C3). 2. Implement linear value function approximators (C3). 3. Explore integration of supervised and reinforcement learning (C5).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-

Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	*
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Reinforcement Learning: An Introduction, Richard S. Sutton and Andrew G. Barto, MIT Press, 2nd Edition – Available online at https://web.stanford.edu/class/psych209/Readings/SuttonBartoIPRLBook2ndEd.pdf 2. Lecture slides of Prof. Emma Brunskill – Stanford University – Available online at http://web.stanford.edu/class/cs234/schedule.html 3. Generative Deep Learning: Teaching Machines to Paint, Write, Compose, and Play, David Foster – O'Reilly, 1st Edition, 2019. 4. Reinforcement Learning and Optimal Control, Dimitri Bertsekas, Athena Scientific; 1st Edition, 2019.

Name of the Program:	ME in Machine Learning
Course Title:	Applied Mathematics for Machine Learning

MANIPAL
ACADEMY *of* HIGHER EDUCATION
(Deemed to be University under Section 3 of the UGC Act, 1956)

Course Code: MCL 616	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 3	**Prerequisites:** MCL 601, 603, 605

Synopsis:	This course provides a comprehensive theoretical foundation in advanced mathematical concepts essential for developing and analysingstate of the art machine learning algorithms.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Develop a solid understanding of fundamentals of matrix decomposition techniques and apply them to practical problems.
CO 2:	Differentiate matrix decomposition techniques and assess their applicability.
CO 3:	Describe the role of derivatives in machine learning and understand different methods for computing them.
CO 4:	Formulate an application problem as a continuous optimization problem.
CO 5:	Acquire solid foundation in understanding the principles behind state-of-the-art optimization algorithms used in machine learning libraries.

Mapping of COs to Pos

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*								
CO 2	*	*									
CO 3	*		*								
CO 4		*	*	*		*					
CO 5		*	*	*	*				*		

Course content and outcomes:

Content	***Competencies***
Unit 1: Matrix Decompositions and Applications	
Matrix and tensor products - Determinant and trace - Eigendecomposition and diagonalization - Cholesky decomposition - Singular value decomposition - Nonnegative matrix factorization.	1. Develop ideas for matrix decompositions using block matrix representations (C5). 2. Compare and contrast exact and approximate decompositions in terms of construction and applications. 3. Understand the optimization-centric view to matrix factorization (C3).

	4. Interpret the factors arising out of matrix factorizations for real-life problems (C3).
Unit 2:Computing Derivatives	
Differentiability - Symbolic differentiation - Finite differences - Automatic differentiation.	1. Understand multivariable differentiability theory (C3). 2. Understand the basics of symbolic differentiation (C3). 3. Develop ideas for approximating derivatives using finite differences (C5). 4. Understand the basics of automatic differentiation and compare it with other approaches (C3, C6).
Unit 3:Continuous Optimization	
Optimization using gradient descent - Constrained optimization and Lagrange multipliers - Convex optimization – Sub gradients - Stochastic gradient descent - Momentum methods.	1. Understand the basics of continuous optimization (C3). 2. Visualize constrained optimization problems and solutions in 3D (C3). 3. Understand convexity and its importance in machine learning (C3). 4. Understand gradient descent method and its extensions for continuous optimization (C4).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-

Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:	
Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos					
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	10. Mathematics for Machine Learning by Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong – Online resource from Cambridge University Press available at https://mml-book.github.io/book/mml-book.pdf 11. Matrix Computations, Gene H. Golub and Charles F. Van Loan, Hindustan Book Agency; 4th Edition, 2015. 12. Deep Learning, Ian Goodfellow, Yoshua Bengio, and Aaron Courville, MIT Press,2017. – Available online at http://www.deeplearningbook.org/ 13. Understanding Machine Learning: From Theory to Algorithms (UML), Shai Shalev-Shwartz and Shai Ben-David, Cambridge University Press, 1st Edition, 2014.

Name of the Program:	ME in Machine Learning
Course Title:	Applied Mathematics for Machine Learning Lab
Course Code:MCL 616L	**Course Instructor:**

Academic Year: 2020-2021	**Semester:**First Year, Semester 2
No of Credits: 1	**Prerequisites:**MCL 616
Synopsis:	This course provides a comprehensive computational foundation in advanced mathematical concepts essential for developing and analysingstate of the art machine learning algorithms.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Implement and compare matrix decomposition techniques.
CO 2:	Assess applicability of matrix decomposition techniques for practical problems.
CO 3:	Implement and compare different methods for computing derivatives.
CO 4:	Implement solutions for real-life problems formulated as a continuous optimization problem.
CO 5:	Understand the implementations ofstate-of-the-art optimization algorithms used in machine learning libraries.

Mapping of COs to Pos

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*		*						
CO 2	*	*	*		*						
CO 3	*	*	*	*	*						
CO 4	*	*	*	*	*	*					
CO 5				*	*						

Course content and outcomes:

Content	***Competencies***
Unit 1: Matrix Decompositions and Applications	
Matrix and tensor products - Determinant and trace - Eigendecomposition and diagonalization - Cholesky decomposition - Singular value decomposition - Nonnegative matrix factorization.	1. Implement matrix decompositions using block matrix representations (C3). 2. Implement and compare exact and approximate decompositions (C6). 3. Implement codes to understand the optimization-centric view to matrix factorization (C3).

	4. Interpret the factors arising out of matrix factorizations for real-life problems (C3).
Unit 2:Computing Derivatives	
Differentiability - Symbolic differentiation - Finite differences - Automatic differentiation.	1. Visualize differentiability concepts in 3D (C4). 2. Implement symbolic differentiation for computing derivatives exactly (C3). 3. Implement finite difference methods for approximating derivatives (C3). 4. Implement automatic differentiation and compare it with other approaches (C3, C6).
Unit 3:Continuous Optimization	
Optimization using gradient descent - Constrained optimization and Lagrange multipliers - Convex optimization – Sub gradients - Stochastic gradient descent - Momentum methods.	1. Solve continuous optimization problems using state of the art libraries (C3). 2. Visualize constrained optimization problems and solutions in 3D (C3). 3. Implement and visualize solutions of gradient descent method and its extensions for continuous optimization (C4). 4. Understand implementations of continuous optimization algorithms used in state-of-the-art libraries (C4).

Learning strategies, contact hours and student learning time		
Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-

Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	*
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process

- Mid-Semester feedback
- End-Semester Feedback

Reference Material

1. Mathematics for Machine Learning by Marc Peter Deisenroth, AAldo Faisal, and Cheng Soon Ong – Online resource from Cambridge University Press available at https://mml-book.github.io/book/mml-book.pdf
2. Matrix Computations, Gene H. Golub and Charles F. Van Loan, Hindustan Book Agency; 4th Edition edition, 2015.
3. Deep Learning, Ian Goodfellow, Yoshua Bengio, and Aaron Courville, MIT Press,2017. – Available online at http://www.deeplearningbook.org/
4. Understanding Machine Learning: From Theory to Algorithms (UML), Shai Shalev-Shwartz and Shai Ben-David, Cambridge University Press, 1st Edition, 2014.

Name of the Program:	ME in Machine Learning
Course Title:	Natural Language Processing Principles & Applications

Course Code: MCL 617	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 3	**Prerequisites:** MCL 601, 603

Synopsis:	This course provides a thorough introduction to fundamental concepts and modern algorithms in natural language processing.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Gain a thorough introduction to fundamental concepts and ideas in natural language processing.
CO 2:	Develop an in-depth understanding of both algorithms for processing linguistic information and the underlying computational properties of natural languages.
CO 3:	Analyse word-level, syntactic, and semantic processing from both a linguistic and an algorithmic perspective.
CO 4:	Formulate deep learning approaches for natural language processing tasks.
CO 5:	Develop practical experience with state-of-the-art natural language processing tools and libraries.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2	*			*							
CO 3	*	*	*	*							
CO 4		*	*	*	*						
CO 5		*	*	*	*				*		

Course content and outcomes:

Content	*Competencies*
Unit 1: Introduction to Natural Language Processing (NLP); Regular Expressions; N-gram Language Models	
Terminology - Probability and NLP Introduction to regular expressions - Information extraction using regular expressions.	1. Understand the basics of NLP and role of probability in it (C3). 2. Understand how to use and apply regular expressions (C3). 3. Develop the idea of a probabilistic language model (C5).

Probabilistic language model - Chain rule and Markov assumption - Evaluating language models – Smoothing.	4. Understand how to evaluate and compare language models (C6).
Unit 2:Naive Bayes and Sentiment Classification; Vector Semantics and Embeddings	
Vector semantics - Words and vectors - Cosine for measuring similarity - TF-IDF vector model - Word2Vec & GloVe models - Visualizing embeddings.	1. Understand how to perform sentiment classification (C4). 2. Develop ideas for vector representation of words (C5). 3. Understand and compare vector models for words (C6). 4. Understand how to visualize word embeddings (C3).
Unit 3:NLP with Deep Learning; Applications of Natural Language Processing	
Neural language models - Introduction to PyTorch -Sequence processing with recurrent neural networks	1. Understand how deep learning can be used for NLP applications (C3). 2. Gain experience in using PyTorch (C3). 3. Understand how recurrent neural networks can be used for NLP applications (C4). 4. Explore practical applications of NLP (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-

TOTAL	**44**	**74**

Assessment Methods:	
Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. Speech and Language Processing, Dan Jurafsky and James H. Martin, Pearson; 3rd Edition (draft) – Available online at https://web.stanford.edu/~jurafsky/slp3/ 2. Natural Language Processing with Python. – Analysing Text with the Natural Language Toolkit, Steven Bird, Ewan Klein, and Edward Loper, ISTE Ltd., 1st Edition, 2017 - Available online at https://www.nltk.org/book/ 3. A Primer on Neural Network Models for Natural Language Processing, Yoav Goldberg – Available online at http://faculty.cse.tamu.edu/huangrh/Spring18/nnlp.pdf 4. Natural Language Processing with PyTorch, Delip Rao & Brian McMahan,O'Reilly, 1st Edition, 2019.

Name of the Program:	ME in Machine Learning

MANIPAL ACADEMY of HIGHER EDUCATION

(Deemed to be University under Section 3 of the UGC Act, 1956)

Course Title:	Natural Language Processing Principles and Applications Lab
Course Code: MCL 617L	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 1	**Prerequisites:** MCL 617

Synopsis:	This course provides a thorough computational foundation to the applications of algorithms for natural language processing.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Gain a thorough introduction to fundamental concepts and ideas in natural language processing.
CO 2:	Develop an in-depth understanding of both algorithms for processing linguistic information and the underlying computational properties of natural languages.
CO 3:	Analyse word-level, syntactic, and semantic processing from both a linguistic and an algorithmic perspective.
CO 4:	Formulate deep learning approaches for natural language processing tasks.
CO 5:	Develop practical experience with state-of-the-art natural language processing tools and libraries.

Mapping of COs to Pos

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*		*						
CO 2	*	*	*		*						
CO 3	*	*	*	*	*						
CO 4	*	*	*	*	*						
CO 5				*	*						

Course content and outcomes:

Content	*Competencies*
Unit 1: Introduction to Natural Language Processing (NLP); Regular Expressions; N-gram Language Models	
Terminology - Probability and NLP Introduction to regular expressions - Information extraction using regularexpressions.	1. Understand the basics of NLP and role of probability in it (C3). 2. Understand how to use and apply regular expressions (C3).

Probabilistic language model - Chain rule and Markov assumption - Evaluating language models – Smoothing.	3. Develop the idea of a probabilistic language model (C5). 4. Understand how to evaluate and compare language models (C6).
Unit 2:Naive Bayes and Sentiment Classification; Vector Semantics and Embeddings	
Vector semantics - Words and vectors - Cosine for measuring similarity - TF-IDF vector model - Word2Vec & GloVe models - Visualizing embeddings.	1. Implement sentiment classification using real-life datasets (C3). 2. Implement building blocks for vector representation of words (C5). 3. Implement and compare vector models for words (C6). 4. Visualize word embeddings (C3).
Unit 3:NLP with Deep Learning; Applications of Natural Language Processing	
Neural language models - Introduction to PyTorch -Sequence processing with recurrent neural networks	1. Implement neural models for NLP applications (C3). 2. Gain experience in using PyTorch (C3). 3. Implement recurrent neural network models for NLP applications (C3). 4. Explore practical applications of NLP (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-

Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	*
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process

- Mid-Semester feedback
- End-Semester Feedback

Reference Material

1. Speech and Language Processing, Dan Jurafsky and James H. Martin, Pearson; 3rd Edition (draft) – Available online at https://web.stanford.edu/~jurafsky/slp3/
2. Natural Language Processing with Python. – Analysing Text with the Natural Language Toolkit, Steven Bird, Ewan Klein, and Edward Loper, ISTE Ltd., 1st Edition, 2017 - Available online at https://www.nltk.org/book/
3. A Primer on Neural Network Models for Natural Language Processing, Yoav Goldberg – Available online at http://faculty.cse.tamu.edu/huangrh/Spring18/nnlp.pdf
4. Natural Language Processing with PyTorch, Delip Rao & Brian McMahan,O'Reilly, 1st Edition, 2019.

Name of the Program:	ME in Machine Learning
Course Title:	Convolutional Neural Networks for Computer Vision
Course Code: MCL 618	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 3	**Prerequisites:** MCL 601, 603

Synopsis:	This course provides a theoretical foundation for the application of convolutional neural networks to computer vision.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Understand the difference between image processing and computer vision.
CO 2:	Understand the theory behind CNNs and to gain hands-on experience on the application of CNNs in computer vision.
CO 3:	Analyse a real-life problem involving computer vision and solve it using CNNs.
CO 4:	Decide how to choose an existing CNN architecture for an application problem.
CO 5:	Develop practical experience with state-of-the-art deep learning tools and libraries.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2	*	*	*								
CO 3		*	*		*						
CO 4		*	*	*	*						
CO 5		*	*	*	*	*			*		

Course content and outcomes:

Content	***Competencies***
Unit 1: Introduction to Computer Vision; Features; Neural Networks Basics	
Computer vision overview - Historical context and applications - Image processing vs. computer vision Histogram of oriented gradients (HOG) - Scale-invariant feature transform (SIFT) - Speeded-up robust features (SURF) - Limitations of hand-engineered features.	1. Compare and contrast computer vision and image processing (C6). 2. Understand how to build features in the context of computer vision (C4). 3. Compare and contrast different types of features for computer vision (C6). 4. Extend ideas from neural networks to computer vision (C2).

Multi-layer perceptron: architecture and parameter learning.	
Unit 2:Convolutional Neural Networks (CNN)	
Network layers: pre-processing, convolutional layers, pooling layers, nonlinearity, fully connected layers, region of interest pooling - Loss functions: hinge loss, squared hinge loss, cross-entropy loss, Euclidean loss, L1 error.	1. Understand the building blocks of a CNN (C4). 2. Understand the purpose and interconnectivity of different types of CNN layers (C4). 3. Understand the role of nonlinear activation functions in a CNN (C4). 4. Understand different types of loss functions used in a CNN (C4).
Unit 3:CNN Learning; Visualizing and Understanding CNNs	
Weight initialization – Regularization - Gradient based learning: batch-, stochastic-, and mini-batch gradient descent, gradient computations in CNN.	1. Understand the importance of random initialization of weights in a CNN (C2). 2. Understand the role of regularization in preventing overfitting (C4). 3. Understand different gradient-based approaches for optimization (C2). 4. Understand how gradients can be efficiently computed in a CNN (C4).
Unit 4:CNN Architectures; Applications of CNNs in Computer Vision	
Image classification, Object detection and localization.	1. Explore the building blocks of state-of-the-art CNN architectures (C4). 2. Explore applications of CNNs to real life problems (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02

Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2		*	*	*	
Assignment/Presentation	*	*	*	*	*
End Semester Examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback
Reference Material	1. A Guide to Convolutional Neural Networks for Computer Vision, Salman Khan, Hossein Rahmani, Syed Afaq Ali Shah, and Mohammed Bennamoun, Morgan & Claypool Publishers, 2018. 2. Lecture slides of Prof. Fei-Fei Li – Stanford University – Available online at http://cs231n.stanford.edu/ 3. Neural Networks and Deep Learning, Michael Nielsen, Determination Press – Available online at http://neuralnetworksanddeeplearning.com/index.html 4. Computer Vision: Algorithms and Applications, Richard Szeliski, Springer, 2011 – Online resource from Springer available at http://szeliski.org/Book/

Name of the Program:	ME in Machine Learning
Course Title:	Convolutional Neural Networks for Computer Vision Lab
Course Code: MCL 618L	**Course Instructor:**
Academic Year: 2020-2021	**Semester:** First Year, Semester 2
No of Credits: 1	**Prerequisites:** MCL 618
Synopsis:	This course provides a computational foundation for the application of convolutional neural networks to computer vision.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1:	Implement image processing and computer vision tasks.
CO 2:	Apply CNNs for computer vision problems.
CO 3:	Analyse a real-life problem involving computer vision and solve it using CNNs.
CO 4:	Use existing state of the art CNN architectures for application problems.
CO 5:	Develop practical experience with state-of-the-art deep learning tools and libraries.

Mapping of COs to Pos

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*	*	*		*						
CO 2	*	*	*		*						
CO 3	*	*	*	*	*						
CO 4	*	*	*	*	*						
CO 5				*	*				*		

Course content and outcomes:

Content	*Competencies*
Unit 1: Introduction to Computer Vision; Features; Neural Networks Basics	
Computer vision overview - Historical context and applications - Image processing vs. computer vision Histogram of oriented gradients (HOG) - Scale-invariant feature transform (SIFT) - Speeded-up robust features	1. Implement basic computer vision and image processing tasks (C3). 2. Build features in the context of computer vision (C3). 3. Compare and contrast different types of features for computer vision (C6).

(SURF) - Limitations of hand-engineered features. Multi-layer perceptron: architecture and parameter learning.	4. Implement and extend ideas from neural networks to computer vision (C3).
Unit 2:Convolutional Neural Networks (CNN)	
Network layers: pre-processing, convolutional layers, pooling layers, nonlinearity, fully connected layers, region of interest pooling - Loss functions: hinge loss, squared hinge loss, cross-entropy loss, Euclidean loss, L1 error.	1. Visualize and understand the building blocks of a CNN (C4). 2. Implementdifferent types of CNN layers and understand their utility (C4). 3. Implement different nonlinear activation functions, compare and contrast them (C6). 4. Implement and understand the role of different types of loss functions used in a CNN (C4).
Unit 3:CNN Learning; Visualizing and Understanding CNNs	
Weight initialization – Regularization - Gradient based learning: batch-, stochastic-, and mini-batch gradient descent, gradient computations in CNN.	1. Implement random initialization of weights in a CNN and compare it with a non-random initialization (C6). 2. Implement regularization to prevent overfitting in CNNs (C3). 3. Implement different gradient-based approaches for optimization (C3). 4. Implement efficient gradient computations in CNNs (C4).
Unit 4:CNN Architectures; Applications of CNNs in Computer Vision	
Image classification, Object detection and localization.	1. Explore the building blocks of state-of-the-art CNN architectures (C4). 2. Explore applications of CNNs to real life problems (C3).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*

Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	*
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process

- Mid-Semester feedback
- End-Semester Feedback

Reference Material

1. A Guide to Convolutional Neural Networks for Computer Vision, Salman Khan, Hossein Rahmani, Syed Afaq Ali Shah, and Mohammed Bennamoun, Morgan & Claypool Publishers, 2018.
2. Lecture slides of Prof. Fei-Fei Li – Stanford University – Available online at http://cs231n.stanford.edu/
3. Neural Networks and Deep Learning, Michael Nielsen, Determination Press – http://neuralnetworksanddeeplearning.com/index.html

	4. Computer Vision: Algorithms and Applications, Richard Szeliski, Springer, 2011

Name of the Program:	ME in Machine Learning
Course Title:	Entrepreneurship
Course Code: ENP 601	**Course Instructor:**
Academic Year:2020 -2021	**Semester:**First Year, Semester 2
No of Credits:3	**Prerequisites:**

Synopsis:	This course introduces students to the theory of entrepreneurship and its practical implementation. It focuses on different stages related to the entrepreneurial process, including business model innovation, monetization, small business management as well as strategies that improve performance of new business ventures. Centred on a mixture of theoretical exploration as well as case studies of real-world examples and guest lectures, students will develop an understanding of successes, opportunities and risks of entrepreneurship. This course has an interdisciplinary approach and is therefore open to students from other Majors.
Course Outcomes (COs):	On successful completion of this course, students will be able to:
CO 1	Understand the basics of entrepreneurial skills and competencies for creation of new ventures.
CO 2	Familiarize with the concept and overview of entrepreneurship with a view to enhance entrepreneurial talent.
CO 3	Appraise the entrepreneurial process starting with pre-venture stage.
CO 4	Create and exploit innovative business ideas and market opportunities.
CO 5	Build a mind-set focusing on developing novel and unique approaches to market opportunities.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2				*							
CO 3			*								
CO 4						*					
CO 5								*			

Course content and outcomes:

Content	***Competencies***

Unit 1: Introduction to Entrepreneurship	
Meaning and Definition of Entrepreneurship-Employment vs Entrepreneurship, Theories of Entrepreneurship, approach to entrepreneurship, Entrepreneur vs.Manager	1. Explain the meaning of Entrepreneurship (C1). 2. Discuss the theories of Entrepreneurship (C1). 3. Discuss the approaches to Entrepreneurship (C1).
Unit 2: Entrepreneurial Traits	
Personality of an entrepreneur, Types of Entrepreneurs	1. Discuss the personality traits of entrepreneurs (C2).
Unit 3: Process of Entrepreneurship	
Factors affecting Entrepreneurship process	1. Identify the fundamentals and responsibilities of entrepreneurship (C2). 2. Exemplify one’s capabilities in relation to the rigors of successful ventures (C3). 3. Identify and differentiates the distinctive characteristics and competencies of an entrepreneurs (C2).
Unit 4: Business Start-up Process	
Idea Generation, Scanning the Environment, Macro and Micro analysis	1. Explain the Process of Business start-up (C1). 2. Develop creativity and critical thinking in identifying opportunities (C5). 3. Apply innovative approaches in envisioning one's entrepreneurial career (C3).
Unit 5: Business Plan Writing	
Points to be considered, Model Business plan	1. Identify different business models (C3). 2. Describe various parts of a business plan(C2).
Unit 6: Case studies	
Indian and International Entrepreneurship	1. Perform self-assessment and analyse entrepreneurial personal traits and competencies (C4).

	2. Evaluate oneself and plan courses of action to help develop one's entrepreneurial characteristics and competencies (C5).

Learning strategies, contact hours and student learning time		
Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	30	60
Quiz	02	04
Small Group Discussion (SGD)	02	02
Self-directed learning (SDL)	-	04
Problem Based Learning (PBL)	02	04
Case Based Learning (CBL)	-	-
Revision	02	-
Assessment	06	-
TOTAL	**44**	**74**

Assessment Methods:	
Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos						
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5	CO 6
Sessional Examination 1	*	*				
Sessional Examination 2			*	*		
Assignment/Presentation					*	*
End Semester Examination	*	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback

MANIPAL ACADEMY of HIGHER EDUCATION
(Deemed to be University under Section 3 of the UGC Act, 1956)

Reference Material	1. NVR Naidu and T. Krishna Rao, "Management and Entrepreneurship", IK International Publishing House Pvt. Ltd 2008. *2.* Mohanthy Sangram Keshari, "Fundamentals of Entrepreneurship", PHI Publications, 2005 *3.* Butler, D. (2006). Enterprise planning and development. USA: Elsevier Ltd. Gerber, M.E. (2008) Awakening the entrepreneur within. NY: Harper Collins.

MANIPAL ACADEMY of HIGHER EDUCATION
(Deemed to be University under Section 3 of the UGC Act, 1956)
INSPIRED BY LIFE

Name of the Program:	ME in Machine Learning
Course Title:	Entrepreneurship Lab
Course Code:ENP 601L	**Course Instructor:**
Academic Year: 2020-2021	**Semester:**First Year, Semester 2
No of Credits: 1	**Prerequisites:**MCL 618

Synopsis:	This course introduces students to the theory of entrepreneurship and its practical implementation. It focuses on different stages related to the entrepreneurial process, including business model innovation, monetization, small business management as well as strategies that improve performance of new business ventures. Centred on a mixture of theoretical exploration as well as case studies of real-world examples and guest lectures, students will develop an understanding of successes, opportunities and risks of entrepreneurship. This course has an interdisciplinary approach and is therefore open to students from other majors.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1	Understand the basics of entrepreneurial skills and competencies for creation of new ventures.
CO 2	Familiarize with the concept and overview of entrepreneurship with a view to enhance entrepreneurial talent.
CO 3	Appraise the entrepreneurial process starting with pre-venture stage.
CO 4	Create and exploit innovative business ideas and market opportunities.
CO 5	Build a mind-set focusing on developing novel and unique approaches to market opportunities.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*										
CO 2				*							
CO 3			*								
CO 4						*					
CO 5								*			

Course content and outcomes:

Content	*Competencies*
Unit 1: Introduction to Entrepreneurship	
Meaning and Definition of Entrepreneurship-Employment vs	1. Explain the meaning of Entrepreneurship (C1).

Entrepreneurship, Theories of Entrepreneurship, approach to entrepreneurship, Entrepreneur vs.Manager	2. Discuss the theories of Entrepreneurship (C1). 3. Discuss the approaches to Entrepreneurship (C1).
Unit 2: Entrepreneurial Traits	
Personality of an entrepreneur, Types of Entrepreneurs	1. Discuss the personality traits of entrepreneurs (C2).
Unit 3: Process of Entrepreneurship	
Factors affecting Entrepreneurship process	1. Identify the fundamentals and responsibilities of entrepreneurship (C2). 2. Exemplify one's capabilities in relation to the rigors of successful ventures (C3). 3. Identify and differentiates the distinctive characteristics and competencies of an entrepreneurs (C2).
Unit 4: Business Start-up Process	
Idea Generation, Scanning the Environment, Macro and Micro analysis	1. Explain the Process of Business start-up (C1). 2. Develop creativity and critical thinking in identifying opportunities (C5). 3. Apply innovative approaches in envisioning one's entrepreneurial career (C3).
Unit 5: Business Plan Writing	
Points to be considered, Model Business plan	1. Identify different business models (C3). 2. Describe various parts of a business plan(C2).
Unit 6: Case studies	
Indian and International Entrepreneurship	1. Perform self-assessment and analyse entrepreneurial personal traits and competencies (C4). 2. Evaluate oneself and plan courses of action to help develop one's entrepreneurial characteristics and competencies (C5).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	12	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	-	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	03	-
Clinic	-	-
Practical	24	-
Revision	03	-
Assessment	06	-
TOTAL	**48**	**-**

Assessment Methods:

Formative:	**Summative:**
Internal practical Test	Sessional examination
Theory Assignments	End semester examination
Lab Assignment & Viva	Viva

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Sessional Examination 1	*	*			
Sessional Examination 2			*	*	*
Assignment/Presentation	*	*	*	*	*
Laboratory examination	*	*	*	*	*

Feedback Process	• Mid-Semester feedback • End-Semester Feedback

Reference Material	1. NVR Naidu and T. Krishna Rao, "Management and Entrepreneurship", IK International Publishing House Pvt. Ltd 2008. 2. Mohanthy Sangram Keshari, "Fundamentals of Entrepreneurship", PHI Publications, 2005 3. Butler, D. (2006). Enterprise planning and development. USA: Elsevier Ltd. Gerber, M.E. (2008) Awakening the entrepreneur within. NY: Harper Collins.

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Name of the Program:	ME in Machine Learning
Course Title:	Mini Project - 2
Course Code: MCL 696	**Course Instructor:**
Academic Year:2020 -2021	**Semester:**First Year, Semester 2
No of Credits: 4	**Prerequisites:** Programming in Python / R

Synopsis:	Students are expected to select a problem in the area of their interest and the area of their specialization that would require an implementation in hardware / software or both in a semester
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1	Apply the objectives of the project work and provide an adequate background with a detailed literature survey
CO 2	Breakdown the project into sub blocks with sufficient details to allow the work to be reproduced by an independent researcher
CO 3	Compose hardware/software design, algorithms, flowchart, methodology, and block diagram
CO 4	Evaluate the results
CO 5	Summarize the work carried out

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1				*							
CO 2					*			*			
CO 3							*			*	
CO 4						*					*
CO 5							*				

Course content and outcomes:

Content	***Competencies***
Phase 1	
Problem identification, synopsis submission, status submission, mid evaluation.	At the end of the topic student should be able to: 1. Identify the problem/specification (C1) 2. Discuss the project (C2)

	3. Prepare the outline (C3) 4. Describe the status of the project (C2) 5. Prepare a mid-term project presentation report (C3) 6. Prepare and present mid-term project presentation slides (C3, C5) 7. Develop project implementation in hardware/software or both in chosen platform (C5)
Phase 2	
Status submission, final evaluation.	1. Prepare the progress report (C3) 2. Prepare the final project presentation report (C3) 3. Prepare and present final project presentation slides (C3, C5) 4. Modify and Develop implementation in hardware/software or both in chosen platform (C3, C5) 5. Justify the methods used and obtained results (C6)

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	-	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	48	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	-	-
Clinic	-	-
Practical	-	-

Revision	-	-
Assessment	03	-
TOTAL	**51**	**09**

Assessment Methods:	
Formative:	**Summative:**
Project Problem Selection	Mid-Term Presentation
Synopsys review	Second status review
First status review	Demo & Final Presentation

Mapping of assessment with Cos

Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Mid Presentation	*	*			
Presentation	*	*	*	*	*

Feedback Process	• End-Semester Feedback
Reference Material	Particular to the chosen project

Name of the Program:	ME in Machine Learning
Course Title:	Seminar - 2
Course Code: MCL 698	**Course Instructor:**
Academic Year:2020 -2021	**Semester:**First Year, Semester 2
No of Credits: 1	**Prerequisites:** Communication Skill

Synopsis:	1. To select, search and learn technical literature. 2. To Identify a current and relevant research topic. 3. To prepare a topic and deliver a presentation. 4. To develop the skill to author a technical report. 5. Develop ability to work in groups to review and modify technical content.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1	Show competence in identifying relevant information, defining and explaining topics under discussion.
CO 2	Show competence in working with a methodology, structuring their oral work, and synthesizing information.
CO 3	Use appropriate registers and vocabulary, and will demonstrate command of voice modulation, voice projection, and pacing.
CO 4	Demonstrate that they have paid close attention to what others say and can respond constructively.
CO 5	Develop persuasive speech, present information in a compelling, well-structured, and logical sequence, respond respectfully to opposing ideas, show depth of knowledge of complex subjects, and develop their ability to synthesize, evaluate and reflect on information.

Mapping of COs to POs

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1	*							*	*		*
CO 2	*							*	*		*
CO 3	*							*	*		*
CO 4	*							*	*		*
CO5	*							*	*		*

Learning strategies, contact hours and student learning time		
Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	-	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	14	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	-	-
Clinic	-	-
Practical	-	-
Revision	-	-
Assessment	-	-
TOTAL	**14**	**-**

Assessment Methods:	
Formative:	**Summative:**
Seminar Topic Selection	
Synopsys review	
PPT Review	

Mapping of assessment with Cos					
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Presentation	*	*	*	*	*

Feedback Process	• End-Semester Feedback
Reference Material	Particular to the chosen Seminar

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Name of the Program:	ME in Machine Learning
Course Title:	Project Work
Course Code: MCL 799	**Course Instructor:**
Academic Year:2020 -2021	**Semester:**Second Year, Semesters 3, 4
No of Credits: 25	**Prerequisites:** SDLC, communication skills, technical skills.
Synopsis:	The project work aims to challenge the student's analytical and creative abilityand to allow the student to synthesize ideas, apply expertise, and insight learned in the student'score discipline. Students build self-confidence, demonstrate independence, and develop professionalism on successfully completion of the project.
Course Outcomes (COs):	On successful completion of this course, students will be able to
CO 1	Successfully acquaint with a working environment and processes that are in place at relevant industries.
CO 2	Familiarize with the challenges as relevant professionals.
CO 3	Review literature and develop solutions for real time onboard projects.
CO 4	Author technical report and deliver presentation.
CO 5	Apply engineering and management principles to achieve project goal.

Mapping of COs to Pos

COs	*PO 1*	*PO 2*	*PO 3*	*PO 4*	*PO 5*	*PO 6*	*PO 7*	*PO 8*	*PO 9*	*PO 10*	*PO 11*
CO 1						*	*	*	*	*	*
CO 2					*						
CO 3	*	*	*	*	*						
CO 4	*	*	*	*							
CO5:						*	*	*	*	*	*

Course content and outcomes:

Content	***Competencies***
Phase 1:	
Problem identification, synopsis submission, status submission, mid evaluation.	At the end of the topic student should be able to: 1. Identify the problem/specification (C1). 2. Discuss the project (C2).

	3. Prepare the outline (C3). 4. Prepare a mid-term project presentation report (C3). 5. Prepare and present mid-term project presentation slides (C3, C5). 6. Develop project implementation in hardware/software or both in chosen platform (C5).
Phase 2	
Status submission, final evaluation.	1. Prepare the progress report (C3). 2. Prepare the final project presentation report (C3). 3. Prepare and present final project presentation slides (C3, C5). 4. Modify and develop implementation in hardware/software or both in chosen platform (C3, C5). 5. Justify the methods used and obtained results (C6).

Learning strategies, contact hours and student learning time

Learning strategy	*Contact hours*	*Student learning time (Hrs)*
Lecture	-	-
Seminar	-	-
Quiz	-	-
Small Group Discussion (SGD)	14	-
Self-directed learning (SDL)	-	-
Problem Based Learning (PBL)	-	-
Case Based Learning (CBL)	-	-
Clinic	-	-
Practical	-	-
Revision	-	-

Assessment	-	-
TOTAL	**14**	**-**

Assessment Methods:	
Formative:	**Summative:**
Project Problem Selection	Mid-Term Presentation
Synopsys review	Second status review
First status review	Demo & Final Presentation

Mapping of assessment with Cos					
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Mid Presentation	*	*			
Presentation	*	*	*	*	*

Feedback Process	• End-Semester Feedback
Reference Material	Particular to the chosen project

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PROGRAM OUTCOMES (PO) AND COURSE OUTCOMES (CO) MAPPING

Sl.No.	Course Code	Course Name	Credits	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11
1	BDA 602	Algorithms and Data Structures for Big Data	3	*	*	*	*					*		
2	MCL 601	Applied Probability & Statistics	3	*	*	*	*		*		*		*	
3	MCL 603	Applied Linear Algebra	3	*	*	*	*	*	*		*			
4	MCL 605	Applied Machine Learning	3	*	*	*	*	*	*		*	*	*	
5		Elective - I	3	*	*	*	*	*	*		*			
6	BDA 602L	Algorithms and Data Structures for Big Data Lab	1	*	*	*		*	*			*		
7	MCL 601L	Applied Probability & Statistics Lab	1	*	*	*	*	*	*		*		*	
8	MCL 603L	Applied Linear Algebra Lab	1	*	*	*	*	*	*					
9	MCL 605L	Applied Machine Learning Lab	1	*	*	*	*	*	*		*	*	*	
10		Elective - I Lab	1	*	*	*	*	*	*		*	*	*	
11	MCL 695	Mini Project - I	4				*	*	*	*	*	*	*	*
12	MCL 697	Seminar - I	1	*							*	*		*
13	MCL 602	Advanced Applications of Probability & Statistics	3	*	*	*	*	*	*		*			
14	MCL 604	Machine Learning Principles & Applications	3	*	*	*	*	*	*		*			

15	MCL 606	Deep Learning	3	*	*	*	*	*	*		*	*		
16	MCL 608	Reinforcement Learning	3	*	*	*	*	*	*					
17		Elective - II	3	*	*	*	*	*	*			*		
18	MCL 602L	Advanced Applications of Probability & Statistics Lab	1	*	*	*	*	*	*		*			
19	MCL 604L	Machine Learning Principles & Applications Lab	1	*	*	*	*	*	*		*		*	
20	MCL 606L	Deep Learning Lab	1	*	*	*	*	*	*		*			
21	MCL 608L	Reinforcement Learning Lab	1	*	*	*	*	*						
22		Elective - II Lab	1	*	*	*	*	*	*					
23	MCL 696	Mini Project - II	4				*	*	*	*	*	*	*	*
24	MCL 698	Seminar - II	1	*							*	*		*
25	MCL799	Project Work	25	*	*	*	*	*	*	*	*	*	*	*