

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 (Machine Learning)



TABLE OF CONTENTS

Contents

NATURE AND EXTENT OF THE PROGRAM	3
PROGRAM EDUCATION OBJECTIVES (PEO)	4
GRADUATE ATTRIBUTES	5
QUALIFICATIONS DESCRIPTORS	7
PROGRAM OUTCOMES	8
COURSE STRUCTURE, COURSEWISE LEARNING OBJECTIVE, AND COURSE OUTCOMES (CO)	9
PROGRAM OUTCOMES (PO) AND COURSE OUTCOMES (CO) MAPPING	29



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 everincreasing 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** (**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
		Acquire in-depth knowledge of specific discipline or
	Scholarship of	professional area, including wider and global perspective,
1		with an ability to discriminate, evaluate, analyse and
	Knowledge	synthesise existing and new knowledge, and integration of
		the same for enhancement of knowledge.
		Analyse complex engineering problems critically, apply
2	Critical Thinking	independent judgement for synthesising information to
2	Critical Thinking	make intellectual and/or creative advances for conducting
		research in a wider theoretical, practical and policy context.
		Think laterally and originally, conceptualise and solve
		engineering problems, evaluate a wide range of potential
2	Problem Solving	solutions for those problems and arrive at feasible, optimal
3		solutions after considering public health and safety,
		cultural, societal and environmental factors in the core areas
		of expertise.
		Extract information pertinent to unfamiliar problems
		through literature survey and experiments, apply
		appropriate research methodologies, techniques and tools,
4	Research Skill	design, conduct experiments, analyse and interpret data,
-	Kesear cii Skiii	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.
		Create, select, learn and apply appropriate techniques,
5	Usage of modern tools	resources, and modern engineering and IT tools, including
5	Usage of modern tools	prediction and modelling, to complex engineering activities
		with an understanding of the limitations.
6	Collaborative and	Possess knowledge and understanding of group dynamics,
6	Multidisciplinary work	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 in order to achieve common goals and
		further the learning of themselves as well as others.
		Demonstrate knowledge and understanding of engineering
		and management principles and apply the same to one's
7	Project Management	own work, as a member and leader in a team, manage
	and Finance	projects efficiently in respective disciplines and
		multidisciplinary environments after consideration of
		economical and financial factors.
		Communicate with the engineering community, and with
		society at large, regarding complex engineering activities
		confidently and effectively, such as, being able to
8	Communication	comprehend and write effective reports and design
		documentation by adhering to appropriate standards, make
		effective presentations, and give and receive clear
		instructions.
		Recognise the need for, and have the preparation and ability
		to engage in life-long learning independently, with a high
9	Life-long Learning	level of enthusiasm and commitment to improve knowledge
		and competence continuously.
		Acquire professional and intellectual integrity, professional
		code of conduct, ethics of research and scholarship,
	Ethical Practices and	consideration of the impact of research outcomes on
10		
	Social Responsibility	professional practices and an understanding of
		responsibility to contribute to the community for
		sustainable development of society.
		Observe and examine critically the outcomes of one's
1		
11	Independent and	actions and make corrective measures subsequently, and
11	Independent and Reflective Learning	actions and make corrective measures subsequently, and learn from mistakes without depending on external



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 a number of advanced and emerging issues in the field of machine learning;

(ii) procedural knowledge that creates different 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 learning and 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 (Machine Learning), students will be able to:

PO	A 44 •1 •4	
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, analyze, 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 prevalant 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 in order 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, team work, 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.



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

FIRST YEAR:

Semester: 1

Semester: 2

Subject Code	Subject Title	L	Т	Р	С	Subject Code	Subject Title	L	Т	Р	С
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	-	I	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 Cre	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	



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 On successful completion of this course, students will be able to (COS): 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 PO 4 PO 5 PO 6 PO 7 PO 8 PO 9 PO 10 PO 11 CO 1 * * CO 3: Design string and text processing programs. Mapping of COs to POs Cos is a string and text processing programs. <	Name	of the P	rogram	:		ME	in Mach	hine	Learnin	g					
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CO 3: techniques. Techniques. Mapping of COs to POs CO 4: Design string and text processing programs. Mapping of COs to POs PO 1 PO 2 PO 3 PO 4 PO 5 PO 6 PO 7 PO 8 PO 9 PO 10 PO 11 CO 1 * * * Image: Colspan="2">PO 10 PO 11 PO 10 PO 11 CO 1 * * * Image: Colspan="2">PO 6 PO 7 PO 8 PO 9 PO 10 PO 11 CO 2 * * *	002.		search	tree, son	rting and	l sea	arching.								
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CO 1*****CO 2*** \cdot \cdot \cdot \cdot CO 3*** \cdot \cdot \cdot \cdot CO 3*** \cdot \cdot \cdot \cdot CO 4*** \cdot \cdot \cdot \cdot CO 4*** \cdot \cdot \cdot \cdot Course content and outcomes:Course content and outcomes:Content															



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

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 Techniq	ues
Quick sort, heap sort, merge sort.	Design applications with suitable sorting and
Linear search and binary search.	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.	Understand and implement BST and its various
Inorder, preorder and postorder	traversal techniques (C2)
traversals.	
Unit 6: Graphs	
Representation of graphs. Depth First	1. Define graphs (C2)
Searching. Breadth First Searching.	2. Design data structure for graphs (C6)
Minimum cost spanning tree.	3. Formulate an algorithm to solve minimum
Single source shortest paths and all-	cost spanning tree(C6)
pairs shortest path.	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 Teo	chniques
Pattern-Matching Algorithms.	1. Design applications with suitable pattern
Text Compression.	matching algorithms (C4).
Tries.	
Unit 8: Data Stream Algorithms	



Sampling, Random Projections,	Basic	1.	Implement	suitable	e data streaming		
Algorithmic Techniques		algorithms (C3).					
Group Testing, Tree Method and	Graph						
sketching.							
Learning strategies, contact hou	irs and	student]	learning tin	ne			
Learning strategy		Conta	ct 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:				Sum	mative:		
Internal practical Test		Sess			ional examination		
Theory Assignments		End			semester examination		
Lab Assignment & Viva		Viva			l		
Mapping of assessment with Co	S						
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	d-Semes	ter feedb	ack	·			
• End	l-Semes	ter Feedl	back				



Reference Material	1. Introduction to Algorithms - Thomas H. Cormen, Charle							
	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												
_							d Data St	U	for Big I	Data Lab		
Course Code: BDA 602L Co					Cou	ourse Instructor:						
Acader	nic Yea	ar: 2020-	2021		Sen	ies	ter: Fi	rst Year, S	Semester	1		
No of (Credits:	: 1			Pre	rea	quisites	: Program	ming in	C or Pyt	hon	
Synop	sis:	This co	ourse ir	ntroduce	es stu	ıde	ents to	elementa	ry data	structur	res and d	esign of
		algoritl	nms. St	udents	learn	h	ow to o	design op	otimal a	lgorithn	ns with re	espect to
		time a	nd spac	ce; imp	leme	ent	link li	ist, stack	, queue	s, searc	hing and	sorting
		technic	lues, se	ets, tree	es an	nd	graphs	; implen	nent str	ing and	l text pr	ocessing
		technic	lues; im	plemen	t dat	a s	tream a	algorithm	s.			
Course	e											
Outco	mes	On suc	cessful	comple	tion	of	this co	urse, stud	lents wi	ll be abl	e to	
(COs):	:											
CO 1:		Evalua	te the p	erforma	ince	of	algorit	nms .				
CO 2:		Develo	p appli	cations	using	g si	uitable	data stru	ctures.			
CO 3:		Design	applica	ations u	sing	da	ta strea	ming and	l pattern	matchi	ng algorit	hms.
Mappi	ing of (COs to 1	POs									
COs	<i>PO</i> 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO	5	PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11
CO 1	*	*	*							*		
CO 2	*	*	*				*					
CO 3	*	*	*		*		*					
Course	e conte	ent and	outcom	es:								
Conter	nt					Competencies						
Unit 1	: Elem	entary]	Data St	ructure	es							
Linked	l List,	Stacks,	Queue	es, Sort	ing	In	npleme	nt Linke	d list, St	acks, Q	ueues (C4	4).
and Se	arching	g Techni	ques			D	esign a	applicatio	ons usin	ıg vario	us search	ing and
						S	orting t	echnique	s.			
Unit 2	: Tree,	Sets an	d Hash	n Table								
Binary	Tree,	Binary s	earch ti	ee		Implement Binary Tree and BST (C4).						
Sets an	Sets and Hash Tables Design applications using Hash Tables											
Unit 3	: Grap	h										
Repres	entatio	n of Gra	nph			In	npleme	ent Grapł	n and it	s traver	sals (BF	S, DFS)
BFS ar	nd DFS					(0	C4).					



Shortest path algorithms	1	Design applications with shortest path algorithms					
		(C4).					
Unit 4: Pattern Matching and	d Data strea	aming					
]	mplement patt	ern matching	g algorithms (C4).			
Learning strategies, contact l	hours and s	tudent learnir	ng time				
Learning strategy		Contact hou	rs	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:			Summa	tivo			
Internal practical Test				al examination			
Theory Assignments				nester examination			
Lab Assignment & Viva			Viva				
			viva				
Mapping of assessment with	Cos						
Nature of assessment	CO 1	CO 2		CO 3			
Sessional Examination 1	*	*					



Assignment/Presentat	ion * * * *							
End Semester Examin	nation	*	*	*				
Laboratory Examination	on	*	*	*				
Feedback Process	• M:	d-Semester f	eedback					
	• En	d-Semester I	Feedback					
Reference Material	1. Da	ta Structure	s and Algorithms in F	Python - Michael T.				
	Go	odrich, Rob	erto Tamassia, and M	ichael H. Goldwasser.				
	Jo	nn Wiley & S	Sons.					
	2. Da	ta Streams	Algorithms and A	Applications - S.				
	M	Muthukrishnan. Foundations and Trends in Theoretical						
	Co	Computer Science archive, Volume 1 Issue 2, August 2005,						
	Pa	ges 117 – 23	6.					



Name o	of the P	rogram	:		ME in	ME in Machine Learning							
Course Title:					Appli	Applied Probability and Statistics							
Name of the Program: N					ME in	n Machii	ne Learr	ning					
		ar: 2020-	-2021					Semester					
No of C								algebra an					
Synop	sis:	This c	ourse p	provides	s an int	roduction	on to fi	undament	al conce	pts in pro	obability		
		and sta	tistics	that are	essent	ial for d	ata scie	nce appli	cations.				
Course													
Outco	mes	On suc	cessfu	l compl	etion of	f this co	ourse, st	udents wi	ill be abl	e to			
(COs):	:												
CO 1:		Unders	stand a	nd appl	y the ba	asic prir	ciples	of sampli	ng.				
CO 2:		Model	randor	n pheno	omena	using ra	ndom v	ariables.					
CO 3:		Calcul	ate & i	nterpret	probal	oility as	a meas	ure of qua	antifying	g uncertai	nty.		
CO 4:		Constr	uct Ba	yesian r	nodels	for anal	ysing p	ractical p	roblems				
CO 5:								hypothesi attributes			ising an		
Mappi	ng of (COs to 2	Pos										
COs	<i>PO</i> 1	<i>PO</i> 2	РО 3	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11		
CO 1	*												
CO 2	*	*	*										
CO 3	*	*	*	*				*					
CO 4		*	*	*		*		*					
CO 5		*	*	*		*				*			
Course	e conte	ent and	outcon	nes:		1					1		
Conten	ıt					Compete	encies						
Unit 1	: Coun	ting; P	robabi	lity Co	ncepts	, Condi	tional I	Probabili	ty				
Multip	licatio	n rul	e; p	ermutat	tion;	1. Und	erstand	and app	ly the b	asic prine	ciples of		
combir	nation	- Samp	ling: w	with/wit	hout	samj	pling (C	C1, C3).					
replace	ement a	und orde	er matte	ers/does	s not 2	2. Und	erstand	and app	ly the b	asic prine	ciples of		
matter	- B	inomial	& 1	nultino	mial	prob	ability	(C1, C3).					
coeffic	ients -	Distribu	ition pi	roblems		3. Diffe	erentiat	e and	relate	frequen	cy-based		
Set the	eory; s	sample	space;	outcon	nes;	es; interpretation of probability to classical							



probability - Equally likely vs. not equally likely outcomes - Axioms of probability4. Apply Bayesian principle for modelling practical problems (C5).Conditional probability; tree model; chain rule - Decomposition and the law of total probability - Bayes' rule - initition, 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 function - Expectation and variance: discrete case - Modelling using distributions; probability density function - Expectation and variance: continuous case - Functions of random variables.1. Understand and differentiate discrete and continuous random variables (C2).Unit 3: Sampling and Parameter Estimution variables.3. Understand how to use random variables to model random phenomena (C4).Vitt 3: Sampling and Parameter Estimution and variance - Central limit theorem - intuition and applications1. 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).	events - Frequency based definition of	approach (C4).
equally likely outcomes - Axioms of probabilitypractical problems (C5).Conditional probability; probability tree model; chain rule - Decomposition and the law of total probability - Bayes' rule - intuition, dependence/independence of events.practical problems (C5).Unit 2: Random VariablesI. Understand and differentiate discrete and continuous random variables of practical interest (C2, C4).Modelling using discrete random variables: Bernoulli, geometric, binomial, negative binomial, hypergeometric, and Poisson function and cumulative distribution function - Expectation and variance: 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; uniform, normal, log-normal, exponential, and beta distribution; probability density function - Expectation and variance: continuous case - Functions of random variables.1. Differentiate population and sample (C4).Vint 3: Sampling and Parameter Estimem and variance - Central limit theorem - intuition and applications1. Differentiate population parameters using inferences drawn from a sample (C6). 3. Design and apply appropriate hypothesis tests for practical problems (C3).Point estimation : Standard error - inturition and applications2. Communicate and explain the results of 4. Communicate and explain the results of		
probabilityConditional probability; probabilityConditional probability; probabilitytree model; chain rule - Decompositionand the law of total probability -Bayes' rule - intuition,dependence/independence of events.Unit 2: Random VariablesModelling using discrete randomModelling using discrete randomvariables: Bernoulli, geometric,binomial, negative binomial,hypergeometric, and Poissonfunction and cumulative distributionfunction - Expectation and variance:discrete case - Modelling usingcontinuous random variables: uniform,normal, log-normal, exponential, andbeta distributions; probability densityfunction - Expectation and variance:continuous case - Functions of randomvariables.Unit 3: Sampling and Parameter EstimetorPopulation and sample - Statistic &nand variance - Central limit theorem -intuition and applicationsPoint estimation - Standard error -Interval estimation: interpretation of4. Communicate and explain the results of		
Conditional probability; tree model; chain rule - Decomposition and the law of total probability - Bayes' rule - intuition, dependence/independence of events.Image: Condition total probability - Bayes' rule - intuition, dependence/independence of events.Unit 2: Random VariablesImage: Condition total probability and bayesImage: Condition total probability - total probability - total probability - total probability and bayesImage: Condition total probability - total probability - total probability and probability and probability and probability and probability and probability and continuous random variables (C2, C4).Image: Condition of the mathematical applicability of probability and probability and probability desity function - Expectation and variance: continuous random variables: uniform, normal, log-normal, exponential, and beta distributions; probability density function - Expectation and variance: continuous case - Functions of random variables.Image: Condition and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem - intuition and applicationsImage: Condition and sample (C4).Point estimation - Standard error - Interval estimation:Image: Condition and sample (C3).Image: Condition and sample (C3).Out al setimation: interval estimation:Standard error - interval estimation:Image: Condition and sample (C3).Image: Condition and sample (C3).Interval estimation:Standard error - interval estimation:Image: Condition and sample (C3).Image: Condition and sample (C3).Interval estimation:Standard error - interval estimation:Image: Condition and sample (C3).Image: Condition and sample (C3).		practical problems (C5).
tree model; chain rule - Decomposition and the law of total probability - Bayes' rule - intuition, dependence/independence of events.Unit 2: Random VariablesModelling using discrete random variables: Bernoulli, geometric, binomial, negative binomial, hypergeometric, and Poisson distributions - Probability mass function and cumulative distribution function - Expectation and variance: 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 interst (C2, C4).Unit 3: Sampling and Parameter Estimation2. Gain solid foundation in the mathematical aspects of random variables (C2).Unit 3: Sampling and Parameter Estimation1. Understand how to use random variables (C6).Population and sample - Statistic & and variance - Central limit theorem – intuition and applications1. Differentiate population and sample (C4).Point estimation - Standard error - Interval estimation: interpretation of1. Describe population parameters using inferences drawn from a sample (C6).Out estimation : interpretation of Hort estimation: interpretation of3. Design and apply appropriate hypothesis tests for practical problems (C3).		
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Bayes' rule - intuition, dependence/independence of events.Intuition, intuition, dependence/independence of events.Unit 2: Random VariablesIntuition, geometric, binomial, negative binomial, hypergeometric, and Poisson function and cumulative distribution function - Expectation and variance: distributions; probability density function - Expectation and variance: continuous random variables: uniform, normal, log-normal, exponential, and beta distributions; probability density function - Expectation and variance: continuous case - Functions of random variables.Inti 3: Sampling and Parameter EstimeVinit 3: Sampling and Parameter Estimation and variance - Central limit theorem – intuition and applications1. Differentiate population parameters using inferences drawn from a sample (C6).9 on testimation - Standard error inturval estimation: interpretation of linterval estimation: interpretation of1. Differentiate and explain the results of somple mean and variance - Central limit theorem – inturiton and applications	tree model; chain rule - Decomposition	
dependence/independence of events.Unit 2: Random VariablesModelling 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 (C2). 3. Understand how to use random variables to model random phenomena (C4).Vint 3: Sampling and Parameter Estimation1. Offerentiate 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).Point estimation - Standard error inturval estimation: interpretation of linterval estimation: interpretation of1. Communicate and explain the results of and explain the results of and explain the results of and explain the results of	and the law of total probability -	
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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 (C2).Unit 3: Sampling and Parameter Estimation and variance - Central limit theorem – intuition and applications1. 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).	dependence/independence of events.	
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binomial, negativebinomial, binomial, hypergeometric, andPoint Poissoninterest (C2, C4).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.3. Understand how to use random variables to model random phenomena (C4).Vint 3: Sampling and Parameter Estimetor4. Compare and contrast practical applicability of random variables (C6).Population and sample - Statistic & and variance - Central limit theorem – intuition and applications1. 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).Point estimation - Standard error - Interval estimation: interpretation of4. Communicate and explain the results of	Modelling using discrete random	1. Understand and differentiate discrete and
hypergeometric,andPoisson2.Gain solid foundation in the mathematical aspects of random variables (C2).distributions- Probability massaspects of random variables (C2).3.Understand how to use random variables to model random phenomena (C4).discretecase- Modellingusing continuous random variables: uniform, normal, log-normal, exponential, and beta distributions; probability density function - Expectation and variance: continuous case - Functions of random variables.4.Compare and contrast practical applicability of random variables (C6).Unit 3: Sampling and Parameter Estimation1.Differentiate population and sample (C4).Population and sample - Statistic & and variance - Central limit theorem - intuition and applications1.Differentiate population parameters using inferences drawn from a sample (C6).Pointestimation - Standard error - Interval estimation: interpretation of4.Communicate and explain the results of	variables: Bernoulli, geometric,	continuous random variables of practical
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.aspects of random variables (C2).Unit 3: Sampling and Parameter Estimation1. Differentiate population and sample (C4).Population and sample - Statistic & and variance - Central limit theorem - intuition and applications1. Differentiate population parameters using inferences drawn from a sample (C6).Point estimation - Standard error - Interval estimation: interpretation of4. Communicate and explain the results of	binomial, negative binomial,	interest (C2, C4).
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.3. Understand how to use random variables to model random phenomena (C4).Unit 3: Sampling and Parameter Estimetion1. Differentiate population and sample (C4).Population and sample - Statistic & and variance - Central limit theorem - intuition and applications1. Differentiate population parameters using inferences drawn from a sample (C6).Point estimation - Standard error - Interval estimation: interpretation of4. Communicate and explain the results of	hypergeometric, and Poisson	2. Gain solid foundation in the mathematical
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.model random phenomena (C4).Unit 3: Sampling and Parameter Estimation1. Differentiate population and sample (C4).Population and sample - Statistic & and variance - Central limit theorem - intuition and applications1. Differentiate population parameters using inferences drawn from a sample (C6).Point estimation - Standard error - Interval estimation: interpretation of4. Communicate and explain the results of	distributions - Probability mass	aspects of random variables (C2).
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normal, log-normal, exponential, and beta distributions; probability density function - Expectation and variance: continuous case - Functions of random variables.Image: Continuous case - Functions of random variables.Unit 3: Sampling and Parameter EstimationImage: Continuous case - Functions of random variables.Image: Continuous case - Functions of random variables.Population and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem - intuition and applicationsImage: Continuous case - Function of the function of	discrete case - Modelling using	4. Compare and contrast practical applicability of
beta distributions; probability density function - Expectation and variance: continuous case - Functions of random variables.Unit 3: Sampling and Parameter EstimationPopulation and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem - intuition and applications1. 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).Point estimation: interpretation of Interval estimation: interpretation of	continuous random variables: uniform,	random variables (C6).
function - Expectation and variance: continuous case - Functions of random variables.Unit 3: Sampling and Parameter EstimationPopulation and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem - intuition and applications1. 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).Point estimation: interpretation of Interval estimation: interpretation of4. Communicate and explain the results of	normal, log-normal, exponential, and	
continuous case - Functions of random variables.Image: Continuous case - Functions of random variables.Unit 3: Sampling and Parameter EstimationImage: Continuous case - Statistic & 1.Differentiate population and sample (C4).Population and sample - Statistic & 1.Differentiate population parameters using inferences drawn from a sample (C6).and variance - Central limit theorem - intuition and applicationsStatistic & 1.Point estimation - Standard error - Interval estimation: interpretation ofStatistic & 1.4.Communicate and explain the results of	beta distributions; probability density	
variables.Unit 3: Sampling and Parameter EstimationPopulation and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem – intuition and applications1. 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).Point estimation: interpretation of Interval estimation: interpretation of4. Communicate and explain the results of	function - Expectation and variance:	
Unit 3: Sampling and Parameter EstimationPopulation and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem – intuition and applications1. 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).Interval estimation: interpretation of4. Communicate and explain the results of	continuous case - Functions of random	
Population and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem – intuition and applications1. 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).Interval estimation: interpretation of4. Communicate and explain the results of	variables.	
 sampling distribution - Sample mean and variance - Central limit theorem – intuition and applications Point estimation - Standard error - Interval estimation: interpretation of 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 	Unit 3: Sampling and Parameter Estin	nation
and variance - Central limit theorem – intuition and applicationsinferences drawn from a sample (C6).3. Design and apply appropriate hypothesis tests for practical problems (C3).Interval estimation: interpretation of4. Communicate and explain the results of	Population and sample - Statistic &	1. Differentiate population and sample (C4).
intuition and applications3. Design and apply appropriate hypothesis testsPoint estimation - Standard error - Interval estimation: interpretation of3. Design and apply appropriate hypothesis tests for practical problems (C3).4. Communicate and explain the results of	sampling distribution - Sample mean	2. Describe population parameters using
Point estimation - Standard error -for practical problems (C3).Interval estimation: interpretation of4. Communicate and explain the results of	and variance - Central limit theorem -	inferences drawn from a sample (C6).
Interval estimation: interpretation of 4. Communicate and explain the results of	intuition and applications	3. Design and apply appropriate hypothesis tests
	Point estimation - Standard error -	for practical problems (C3).
confidence interval - Hypothesis hypothesis testing (C6)	Interval estimation: interpretation of	4. Communicate and explain the results of
All and the second second (co).	confidence interval - Hypothesis	hypothesis testing (C6).



testing: p-values, significance leve	el and						
their interpretations, application	on to						
analysis of one- /two-sample mea	in and						
paired data.							
Learning strategies, contact hou	rs and	student	learning	time			
Learning strategy		Conte	act hours		Stua time	lent learning (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:				Summat	ive:		
Internal practical Test				Sessional	l exam	ination	
Theory Assignments				End seme	ester e	xamination	
Lab Assignment & Viva				Viva			
Mapping of assessment with Cos	S						
Nature of assessment	CO 1	CO 2	CO 3	CO 4		CO 5	
Sessional Examination 1	*	*					
Sessional Examination 2		*	*	*			
Assignment/Presentation	*	*	*	*		*	
End Semester Examination	*	*	*	*		*	
		ter feed ter Feed					



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: N					ME in Machine Learning							
Course Title:				Appl	lied Proba	ability a	nd Statisti	cs Lab				
Course Code:	MCL 60)1L		• • •	rse Instr	-						
Academic Yea	ar: 2020-	-2021		Sem	ester: Fin	st Year,	, Semester	1				
No of Credits:	: 1			Prer	equisites	: MCL	601					
Synopsis:	This c	ourse	provide	es a ha	ands-on	introdu	action to	fundam	ental cor	cepts in		
	probab	oility ar	nd statis	stics th	at are es	sential	for data	science a	applicatio	ons using		
	the R p	progran	nming l	angua	ge.							
Course												
Outcomes	On suc	cessfu	l compl	etion c	of this co	urse, st	udents w	ill be abl	e to			
(COs):												
CO 1:	Apply	the bas	sic prine	ciples of	of sampl	ing to p	practical p	oroblems	•			
CO 2:	Visual	ize pro	bability	conce	pts throu	ugh frec	quency-ba	ased inte	rpretatior	ıs.		
	Simula	ate dise	crete ar	nd con	tinuous	randon	n variabl	es for n	nodelling	random		
CO 3:	phenor	mena.										
CO 4:	Design	and a	pply hy	pothes	is tests f	ollowed	l by inter	pretation	of result	s.		
005	Interpr	et sta	tistical	result	results and communicate them unambiguously and							
CO 5:	effecti	vely.										
Mapping of	COs to 2	POs										
COs PO 1	<i>PO 2</i>	PO	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11		
		3										
CO 1 *	*	*		*								
CO 2	*	*		*								
CO 3 *	*	*	*	*								
CO 4	*	*	*	*	*							
CO 5			*	*	*		*		*			
Course conte	ent and	outcor	nes:	<u>I</u>		<u>I</u>	1		1	<u> </u>		
Content					Compete	encies						
Unit 1: Coun	ting; P	robabi	lity Co	ncepts	; Condi	tional I	Probabili	ity				
Multiplication	n rul	e; p	ermuta	tion;	1. Und	erstand	the ba	sic prin	ciples of	f the R		
combination	- Samp	ling: v	vith/wit	hout	prog	rammiı	ng langua	.ge (C1).				
replacement a	und orde	er matte	ers/does	s not	2. Deve	elop sh	ort code	snippets	to unders	stand the		
replacement and order matters/does not 2. Develop short code snippets to understand matter - Binomial & multinomial basic principles of sampling and probability												



coefficients - Distribution problems		(C1, C3).
Set theory; sample space; outcomes;	3.	Visualise and interpret probability concepts
events - Frequency based definition of		through a frequency-based approach (C6).
probability - Equally likely vs. not	4.	Program and analyse Bayesian models for
equally likely outcomes - Axioms of		practical problems (C4).
probability		
Conditional probability; probability		
tree model; chain rule - Decomposition		
and the law of total probability -		
Bayes' rule - intuition,		
dependence/independence of events.		
Unit 2: Random Variables	1	
Modelling using discrete random	1.	Understand and apply R functions to simulate
variables: Bernoulli, geometric,		discrete and continuous random variables
binomial, negative binomial,		(C3).
hypergeometric, and Poisson	2.	Using sampling, compute and interpret
distributions - Probability mass		different attributes of random variables (C4).
function and cumulative distribution	3.	Visualise and interpret histograms and
function - Expectation and variance:		probability mass/density functions of random
discrete case - Modelling using		variables using state of the art visualisation
continuous random variables: uniform,		libraries in R (C4).
normal, log-normal, exponential, and	4.	Develop codes to model random phenomena
beta distributions; probability density		using appropriate random variables (C5).
function - Expectation and variance:		
continuous case - Functions of random		
variables.		
Unit 3: Sampling and Parameter Estin	nati	Dn
Population and sample - Statistic &	1.	Visualise sample data through histograms
sampling distribution - Sample mean		(C3).
and variance - Central limit theorem -	2.	Compute estimates of population parameters
intuition and applications		using samples and communicate the
Point estimation - Standard error -		uncertainty in the estimates (C4).



Interval estimation: interpretation of	3.	Use R in-built functions for performing						
confidence interval - Hypothesis hypothesis tests (C4).								
testing: p-values, significance level and	4.	Interpret and communicate the results of						
their interpretations, application to		hypothesis tests (C6).						
analysis of one- /two-sample mean and								
paired data								

Learning strategies, contact hours and student learning time Contact hours Student learning *Learning strategy* 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 Examinatio	n 2			*	*					
Assignment/Presentat	ion	*	*	*	*	*				
Laboratory examinati	on	*	*	*	*	*				
Feedback Process	• Mic	l-Seme	ster feedb	back		1				
	• Enc	l-Semes	ster Feed	back						
Reference Material	1. Introdu	ction to	o Probal	oility, Cha	arles M. Grinst	tead, American				
	Mathemati	cal Soc	iety; 2nd	Revised E	Edition 1997. Ava	ailable online at				
	https://oper	n.umn.e	edu/opent	extbooks/t	extbooks/introdu	iction-to-				
	probability									
	2. A First	Course	in Proba	bility, She	eldon Ross, 9th H	Edition, Pearson				
	Education	India; 9	th Editio	n, 2013.						
	3. Biostati	stics C	pen Lea	rning text	tbook – 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, Larr									
	Wasserman	n – Spri	nger.							



Name of t	the P	rogram	:		ME	in Machine	Learnin	g	ME in Machine Learning							
Course T	'itle:				App	Applied Linear Algebra										
Course C		MCL 60)3			Course Instructor:										
Academic	c Yea	r: 2020	-2021		Sem	ester: First	Year, S	emester	1							
No of Cre	No of Credits: 3						Basic alg	gebra and	d calculu	S						
Synopsis	5:	This c	ourse p	rovides	an ir	ntroduction	to fun	damenta	al conce	pts in pr	obability					
		and sta	atistics t	hat are	essen	tial for dat	a scienc	e applic	cations.							
Course																
Outcome	es	On suc	cessful	comple	etion	of this cou	rse, stud	lents wi	ll be abl	e to						
(COs):				I			,									
CO 1:		Unders	stand ho	ow to us	se vec	tors and m	atrices	to mode	el real-li	fe quantit	ies.					
		Develo	op a sol	id unde	rstan	ding of ma	trix-vec	tor ope	rations a	and relate	them to					
CO 2:			fe calcul			0		1								
CO 3:		Apply and analyze algorithms constructed using matrix-vector principles.														
Develop models for						life application	ations u	sing the	e least s	squares to	echnique					
CO 4:	CO 4: and interpret the result						ts from a practical perspective.									
			-		dation for extending matrix-vector principles to modern											
CO 5:			-	-			nunng m	lati ix-ve	ctor pri	nerpies u	mouern					
		machi	ne learn	ing algo	orithn	ns.										
Mapping	g of (COs to	POs													
COs P	01	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO.	5 PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11					
CO 1 *																
CO 2 *		*														
CO 3 *		*	*	*	*			*								
CO 4		*	*	*	*	*		*								
CO 5		*	*	*	*	*										
Course c	conte	ent and	outcom	nes:							<u> </u>					
Content						Competer	cies									
Unit 1: V	Vecto	ors														
Conceptu	ial i	introduc	ction to	o vect	ors;	1. Under	stand th	ne mathe	ematical	l languag	e behind					
vector	ac	ddition;	sc	alar-ve	ctor	vector	s and c	ompare	algebra	nic and g	eometric					
multiplic	ation	ı-Do	ot prod	uct; no	orm;	repres	entation	s of vec	ctors (C2	2, C4).						
distance	-	Stan	dard	deviat	ion;	2. Under	stand m	athema	tical ope	erations i	nvolving					
standardi	zatio	on vs	. nor	malizat	ion;	vector	s and th	neir app	lication	s in real-	life (C2,					



angle between vectors - Application		C3).				
example: k-means clustering algorithm	3.	Construct a clustering alg	gorithm from scratch			
- Linear dependence/independence;		using vector principles and	d operations (C5).			
basis - Orthonormal vectors;	4.	Gain a solid understar	nding of important			
projections; Gram-Schmidt algorithm.		theoretical principles to be	e applied later (C2).			
Unit 2: Matrices						
Conceptual introduction to matrices;	1.	Understand the mathemat	ical language behind			
types of matrices (zero, identity,		matrices and interpret the	em as extensions of			
diagonal) - Addition of matrices;		vectors (C2, C6).				
transpose; norm - Matrix-vector	2.	Understand mathematical	operations involving			
product – concept & examples -		matrices & vectors and	their applications in			
Systems of linear equations: over- &		real-life (C2, C3).				
under-determined systems - Matrix-	3.	Gain a solid understar	nding of important			
matrix product - concept & examples -	theoretical principles involved in solvin					
QR factorization - Solving linear		systems of linear equation	s (C2).			
equations.	4. Develop and interpret matrix factorization as a					
		powerful tool for data anal	lysis (C5, C6).			
Unit 3: Linear Least Squares						
Least squares: problem motivation and	1.	Understand the mathemat	ical setup of a linear			
examples - Solving linear least squares		least squares problem usin	g practical examples			
problems - Least squares data fitting;		(C2).				
validation; feature engineering - Least	2.	Formulate linear least squ	uares problem using			
squares classification		block matrix operations (C	25).			
	3.	Understand how to select	et good features for			
		data fitting using least squ	ares (C2, C6).			
	4.	Construct and compa	re least squares			
		classification with regress	ion (C5, C6).			
Learning strategies, contact hours and	stu	ident learning time				
Learning strategy		Contact hours	Student learning			
			time (Hrs)			
Lecture		30	60			
Quiz	(02	04			
			1			



Small Group Discuss	ion (SGD)		02			02	
Self-directed learning	(SDL)		-			04	
Problem Based Learn	ing (PBL)		02			04	
Case Based Learning	(CBL)		-	-			
Revision			02	02			
Assessment			06			-	
TOTAL			44			74	
Assessment Methods	5:		•			1	
Formative:					Summati	ve:	
Internal practical Test			Sessional	exan	nination		
Theory Assignments			End seme	ster e	examination		
Lab Assignment & V			Viva				
Mapping of assessme	ent with Co	S					
Nature of assessment		CO 1	CO 2	CO 3	CO 4		CO 5
Sessional Examinatio		*	*				
Sessional Examinatio	n 2		*	*	*		
Assignment/Presentat		*	*	*	*		*
End Semester Examin	1	*	*	*	*		*
Feedback Process	• Mie	d-Semes	ster feedl	back			
			ster Feed				
Reference Material							, Matrices, and
	-		-	•			ghe, Cambridge
					Available of	online	e at http://vmls-
	book.stanf		-				
		•				: Stra	ng, CENGAGE
	LEARNIN						
					•		rd Bronson and
					d Edition, 2		
					•		rn Recognition
			•		s Elden – S	ociet	y for Industrial
	and Applie	a Mathe	ematics,	2007.			



Name o	Name of the Program: M						/E in Machine Learning							
Course	Title:				App	pplied Linear Algebra Lab								
Course	Code:	MCL 60)3L			Course Instructor:								
Academ	nic Yea	r: 2020-	2021		Sem	ester: Fir	st Year,	Semester	1					
No of C	Credits:	1			Prei	requisites	: MCL	603						
Synop	sis:	This c	ourse	provide	s a h	ands-on	introdu	iction to	fundam	ental cor	ncepts in			
		linear a	algebra	that ar	e esse	ntial for	data sci	ience appl	lications	using th	e Python			
			-							U	•			
0		programming language.												
Course	e													
Outcon	mes	On suc	On successful completion of this course, students will be able to											
(COs):														
		Develo	p soli	l skills	in us	sing Pvtł	non's le	egacy lib	raries fo	or coding	matrix-			
CO 1:		vector				8 1		8 5		2	2			
<u> </u>			1				•							
CO 2:		Implement algorithms constructed using matrix-vector principles. Implement models for real-life applications using the least squares technique												
CO 3:		Implen	nent m	odels fo	or real	l-life app	lication	s using th	ne least	squares t	echnique			
0.0.5:	and interpret the results from a practical perspective.													
Manni	ng of (COs to]	Pos											
COs	PO 1	PO 2	PO	<i>PO</i> 4	PO 5	F PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11			
COS	FUT	FU2		F04	FUS	FUU	<i>FU</i> /	FUO	109	F0 10	FUII			
			3											
CO 1	*	*												
CO 2		*	*	*	*									
CO 3	*	*	*	*	*	*								
Course	e conte	nt and	outcon	nes:										
Conten						Compete	ncies							
Unit 1		re				compete								
			tion 4		4 a ma s	1 Urad		h						
		introduc						how to p	beriorm	vector of	perations			
vector	a	ddition;	SC	alar-ve	ector	using	g Pytho	n (C2).						
multipl	ication	1 - Do	ot prod	uct; no	orm;	2. Visu	alize v	vectors an	nd relat	te them	to their			
distanc	e -	Stan	dard	devia	tion;	geon	netric d	escription	(C1, C	2).				
standar	dizatio	on vs.	nor	malizat	tion;	3. Impl	ement	the K-	means	algorith	m from			
angle	betwee	n vecto	rs - A	Applica	tion									
example: k-means clustering algorithm														
- Lin	ear c	lepende	nce/ind	epende	nce;	Gran	n-Schm	idt algori	thm (C5	<i>i</i>).				



basis - Orthonormal vectors; projections; Gram-Schmidt algorithm. 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. 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 squares classification squares classification Learning strategy Lecture Learning strategy Lecture Learning strategy Lecture Learning strategy Lecture Seminar Quiz Seminar Quiz Seminar Publem Based Learning (PBL) Contact hours Pathon and set of the se		o oe Oniversity under Section 3 of the OGC Act, 1736)					
Unit 2: Matrices Conceptual introduction to matrices; 1. Understand how to perform matrix operations using Python (C2). 2. Implement and interpret matrix-vector operations using block-matrix operations (C5). product – concept & examples - Systems of linear equations: over- & under-determined systems - Matrix- QR factorization - Solving linear equations. Unit 3: Linear Least Squares problems - Least squares in polython interpret the results (C3). 2. Implement and fine-ture extraction using Python and interpret the results (C3). 2. Implement and fine-ture extraction using least squares for practical problems problems - Least squares data fitting; validation; feature engineering - Least squares classification Contact hours Learning strategies, contact hours and suttent learning time (Hrs) Lecture 12 Seminar - Quiz - Seminar - Quiz - Self-directed learning (PBL) - Cinic - Problem Based Learning (CBL)	· · · · · · · · · · · · · · · · · · ·						
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- requations.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).3. Understand how to solve linear systems of equations using Python (C2).4. Code practical applications of QR factorization - Solving linear equations.4. Code practical applications of QR factorization of matrices (C4). Unit 3: Linear Least Squares problems - Least squares data fitting; validation; feature engineering - Least squares classification1. Solve linear least squares problems using Python and interpret the results (C3). Learning strategies, contact hours and student learning time (Hrs)Learning strategies, contact hours and student learning time (Hrs)Lecture122SeminarQuizSmall Group Discussion (SGD)Self-directed learning (PBL)ClinicClinicClinicClinic	projections; Gram-Schmidt algorithm.						
types of matrices (zero, identity, diagonal) - Addition of matrices; ranspose; norm - Matrix-vector product - concept & examples - Systems of linear equations: over- & under-determined systems - Matrix matrix product - concept & examples - QR factorization - Solving linear equations. 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 Learning strategy Lecture 1 Learning strategy Lecture 1 Seminar - Quiz - Concept (SDL) - Concept	Unit 2: Matrices						
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.2. Implement and interpret matrix-vector operations using block-matrix operations (C5). 3. Understand how to solve linear systems of equations using Python (C2).Unit 3: Linear Least Squares4. Code practical applications of QR factorization of matrices (C4).Unit 3: Linear Least Squares9. Solving linear linear least squaresproblems - Least squares data fitting; validation; feature engineering - Least squares classification1. Solve linear least squares for practical problems (C5). 3. Implement least squares for practical problems (C5). 3. Implement least squares for matrices (C4).Learning strategies, contact hours and student learning time (Learning strategy2. Contact hours im (Hrs)Lecture12-QuizSmall Group Discussion (SGD)Self-directed learning (PBL)Case Based Learning (CBL)03-Clinic	Conceptual introduction to matrices;	1. Understand how to perform matrix operation	ns				
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. Unit 3: Linear Least Squares groblems - Least squares data fitting; validation; feature engineering - Least squares classification teatring strategies, contact hours and Electure 12 Lecture 12 Contact hours 13 Lecture 12 Lecture 12 Lecture 12 Lecture 12 Lecture 12 Lecture 12 Lecture 12 Lecture 12 Lecture 12 Contact hours 13 Lecture 12 Lecture 12 Contact hours 13 Lecture 13 Lecture 14 Lecture 1	types of matrices (zero, identity,	using Python (C2).					
Productconcept & examples3.Understand how to solve linear systems of equations using Python (C2).Systems of linear equations: over- under-determined systems - Matrix matrix product - concept & examples - QR factorization - Solving linear equations.3.Code practical applications of QR factorization of matrices (C4).QR factorization - Solving linear equations.4.Code practical applications of QR factorization of matrices (C4).Unit 3: Linear Least Squares examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification1.Solve linear least squares for practical problems using Python and interpret the results (C3).Learning strategies, contact hours and Learning strategy2.Implement least squares for practical problems (C5).Learning strategyContact hoursStudent learning time (Hrs)Lecture12-SeminarQuizSnall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (CBL)03-Clinic	diagonal) - Addition of matrices;	2. Implement and interpret matrix-vector	or				
Systems of linear equations: over- & under-determined systems - Matrix- matrix product - concept & examples - QR factorization - Solving linear equations.equations using Python (C2).Unit 3: Linear Least Squares examples - Solving linear least squares examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification1. Solve linear least squares problems using Python and interpret the results (C3).2. Implement and fine-tume feature extraction using least squares for practical problems (C5). 3. Implement least squares for practical problems (C5). 3. Implement least squares classification (C3).Learning strategies, contact hours and EatureContact hours imme (Hrs)Learning strategyContact hours imme (Hrs)Lecture12Quiz-Small Group Discussion (SGD)-Problem Based Learning (PBL)-Case Based Learning (CBL)03Clinic-Clinic-	transpose; norm - Matrix-vector	operations using block-matrix operations (C5).				
under-determined systems - Matrix- matrix product - concept & examples - QR factorization - Solving linear equations.4. Code practical applications of QR factorization of matrices (C4).Unit 3: Linear Least Squares5. Solving linear linear least Squares1. Solve linear least squares problems using Python and interpret the results (C3).Least squares: problem motivation and examples - Solving linear least squares1. Solve linear least squares problems using Python and interpret the results (C3).uidation; feature engineering - Least squares classification1. Solve linear least squares for practical problems (C5). 3. Implement least squares for practical problems (C5).Learning strategies, contact hours and Earning strategyContact hoursStudent learning time (Hrs)Lecture12-QuizSeminarQuizSelf-directed learning (SDL)Problem Based Learning (CBL)03-Cinic	product – concept & examples -	3. Understand how to solve linear systems	of				
matrix product - concept & examples - QR factorization - Solving linear equations.factorization of matrices (C4).Ideat factorization - Solving linear equations.Unit 3: Linear Least SquaresLeast squares: problem motivation and examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification1. Solve linear least squares for practical problems (C5). 3. Implement least squares classification (C3).Learning strategies, contact hours and Learning strategyContact hours (C1)Student ime (Hrs)Lecture12-SeminarQuizSnall Group Discussion (SGD)Self-directed learning (DL)Problem Based Learning (CBL)03-ClinicClinic	Systems of linear equations: over- &	equations using Python (C2).					
QR factorization - Solving linear equations.Init 3: Linear Least SquaresUnit 3: Linear Least SquaresLeast squares: problem motivation and examples - Solving linear least squares1. Solve linear least squares problems using Python and interpret the results (C3).problems - Least squares data fitting; validation; feature engineering - Least squares classification2. Implement and fine-tum feature extraction using least squares for practical problems (C5). 3. Implement least squares for practical problems (C5).Learning strategies, contact hours and time there is the learning timeStudent learning time (Hrs)Lecture12-SeminarQuizSnall Group Discussion (SGD)Self-directed learning (DL)Problem Based Learning (CBL)03-ClinicClinic	under-determined systems - Matrix-	4. Code practical applications of Q	R				
equations. equations. Unit 3: Linear Least Squares Least Squares Squares Least Squares Squares problem motivation and examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares of practical problems using least squares for practical problems (C5). 2. Implement least squares for practical problems (C5). guares classification 3. Implement least squares stification (C3). Learning strategies, contact hours and Eventing time Learning strategy Contact hours Student learning time (Hrs) Lecture 12 - Seminar - - - Quiz - - - Small Group Discussion (SGD) - - - Problem Based Learning (PBL) - - - Case Based Learning (CBL) 03 - - Clinic - - - -	matrix product - concept & examples -	factorization of matrices (C4).					
Unit 3: Linear Least SquaresUnit 3: Linear Least SquaresLeast squares Spoblem motivation and examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification1. Solve linear least squares problems using Python and interpret the results (C3).2. Implement and fine-tume feature extraction using least squares for practical problems (C5). 3. Implement least squares classification (C3).Learning strategies, contact hours and Eurore the resultContact hoursStudent learning time (Hrs)Lecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (CBL)03-ClinicClinic	QR factorization - Solving linear						
Least squares: problem motivation and examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification1. Solve linear least squares problems using Python and interpret the results (C3).2. Implement and fine-tume feature extraction using least squares for practical problems (C5). 3. Implement least squares classification (C3).2. Implement least squares for practical problems (C5). 3. Implement least squares classification (C3).Learning strategies, contact hours and student learning time time (Hrs)Student learning time (Hrs)Lecture12-SeminarQuizShall Group Discussion (SGD)Self-directed learning (PBL)Case Based Learning (CBL)03-ClinicClinic	equations.						
examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classificationPython and interpret the results (C3).2. Implement and fine-tune tast squares classification2. 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 time (Hrs)Student tearning time (Hrs)Lecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (CBL)03-ClinicClinic	Unit 3: Linear Least Squares						
problems - Least squares data fitting; validation; feature engineering - Least squares classification2. 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 strategyContact hoursStudent learning time (Hrs)Lecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (CBL)03-ClinicClinic	Least squares: problem motivation and	1. Solve linear least squares problems usin	ıg				
validation; feature engineering - Least squares classificationusing least squares for practical problems (C5). 3. Implement least squares classification (C3).Learning strategies, contact hours and student learning timeStudent learning time (Hrs)Learning strategyContact hoursStudent learning time (Hrs)Lecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (CBL)03-ClinicClinic	examples - Solving linear least squares	Python and interpret the results (C3).					
squares classification(C5). 3. Implement least squares classification (C3).Learning strategies, contact hours and student learning timeStudent learning time (Hrs)Learning strategyContact hoursStudent learning time (Hrs)Lecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (PBL)Case Based Learning (CBL)03-Clinic	problems - Least squares data fitting;	2. Implement and fine-tune feature extraction					
3. Implement least squares classification (C3).Learning strategies, contact hours and student learning timeLearning strategyContact hoursStudent learning time (Hrs)Lecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (PBL)Case Based Learning (CBL)03-Clinic	validation; feature engineering - Least	using least squares for practical problen	ns				
Learning strategies, contact hours and student learning timeLearning strategyContact hoursStudent learning time (Hrs)Lecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (PBL)Case Based Learning (CBL)03-Clinic	squares classification	(C5).					
Learning strategyContact hoursStudent learning time (Hrs)Lecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (PBL)Case Based Learning (CBL)03-Clinic		3. Implement least squares classification (C3).					
ConstraintConstraintLecture12-SeminarQuizSmall Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (PBL)Case Based Learning (CBL)03-Clinic	Learning strategies, contact hours and	student learning time					
Lecture12Seminar-Quiz-Small Group Discussion (SGD)-Self-directed learning (SDL)-Problem Based Learning (PBL)-Case Based Learning (CBL)03Clinic-	Learning strategy	Contact hours Student learnin	ıg				
Seminar-Quiz-Small Group Discussion (SGD)-Self-directed learning (SDL)-Problem Based Learning (PBL)-Case Based Learning (CBL)03Clinic-		time (Hrs)					
Quiz-Small Group Discussion (SGD)-Self-directed learning (SDL)-Problem Based Learning (PBL)-Case Based Learning (CBL)03Clinic-	Lecture	12 -					
Small Group Discussion (SGD)Self-directed learning (SDL)Problem Based Learning (PBL)Case Based Learning (CBL)03-Clinic	Seminar						
Self-directed learning (SDL)Problem Based Learning (PBL)Case Based Learning (CBL)03-Clinic	Quiz						
Problem Based Learning (PBL)Case Based Learning (CBL)03-Clinic	Small Group Discussion (SGD)						
Case Based Learning (CBL)03Clinic	Self-directed learning (SDL)						
Clinic	Problem Based Learning (PBL)						
	Case Based Learning (CBL)	03 -					
Practical 24 -	Clinic						
	Practical	24 -					



Revision			03			-	
Assessment			06			-	
TOTAL			48	48			
Assessment Methods	X•						
Formative:	•				Summati	ve	
Internal practical Test			Sessional		nination		
Theory Assignments	-						xamination
Lab Assignment & V				Viva		Adminiation	
	lva				VIVa		
M							
Mapping of assessme	ent with Co	s CO 1	CO 2				005
	Nature of assessment			CO 3	CO 4		CO 5
Sessional Examinatio		*	*				
Sessional Examinatio				*	*		
Assignment/Presentat	*	*	*	*		*	
Laboratory examinati	on	*	*	*	*		*
Feedback Process	• Mic	d-Semes	ster feed	back			
	• Enc	l-Semes	ster Feed	back			
Reference Material	1. Introdu	ction to	Applie	d Linear	Algebra, Ve	ectors	, Matrices, and
	Least Squa	ares, Ste	ephen B	oyd & L	ieven Vande	enberg	ghe, Cambridge
	University	Press,	1st Editi	ion, 2018	. Available o	online	e at http://vmls-
	book.stanfo	ord.edu/	/vmls.pd	f			
	2. Linear	Algebra	and its	Applicat	ions, Gilbert	t Stra	ng, CENGAGE
	LEARNIN	G (RS)	; 4th Edi	tion, 2005	5.		
	3. Matrix	Method	ls: Appl	ied Linea	r Algebra, F	Richai	rd Bronson and
	Gabriel B.	Costa, A	Academi	c Press; 3	rd Edition, 2	2008.	
	4. Matrix	Metho	ods in	Data Mi	ning and	Patter	n Recognition
	(Fundamer	ntals of	Algoritl	nms), Lar	s Eldén – S	Societ	y for Industrial
	and Applie		-				-
	and Applie	u maine	ematics,	2007.			



Name	of the P	rogram	:		ME in	Machine	Learnin	g					
Course	e Title:				Applie	Applied Machine Learning							
Course	e Code:	MCL 60)5		Course Instructor:								
Acade	mic Yea	ar: 2020-	-2021		Semes	ter: Firs	t Year, S	emester	1				
No of	Credits	: 3			Prere	quisites:	Python p	rogrami	ning				
Synop	sis:	This o	course	provide	es a b	road in	troducti	on to	importa	nt conce	epts and		
		algorit	hms in a	applied	machir	e learni	ng.						
Cours	e												
Outco	mes	On suc	cessful	comple	etion of	this cou	rse, stud	ents wi	ll be abl	e to			
		onsu	cossiai	compie			150, 5144			0 00			
(COs): Develop practical experience with state of the art machine learning tools and													
CO 1:		Develo	op pract	ical exp	perience	e with st	ate of th	ne art m	achine	learning t	cools and		
		librarie	es.										
~ ~ ~		Differe	entiate	between	n differ	rent typ	es of m	nachine	learnin	g paradi	gms and		
CO 2: choose an appropriate one for a given application problem.													
Apply different types of supervised and unsupervised machine									machine	learning			
CO 3:		algorit	hms to j	practica	l proble	ems and	assess tl	heir per	formanc	æ.			
		Unders	stand t	he imn	ortance	of fea	ature en	gineeri	ng in 1	machine	learning		
CO 4:		applica					••••••	.8					
		Acquir	e a soli	d found	ation ir	hasic n	achine	learning	, skills f	or more a	dvanced		
CO 5:		-		a round	ation n	i ousie ii	lucillie	louining	, skins i		u v une eu		
		exposi	tions.										
Mapp	ing of (COs to											
COs	PO 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	<i>PO</i> 8	<i>PO</i> 9	PO 10	PO 11		
CO 1	*				*								
CO 2	*	*	*	*									
CO 3	*	*	*	*		*		*					
CO 4		*	*	*		*				*			
CO 5	*	*	*	*					*				
Cours	e conte	ent and	outcom	ies:	1			1		1	ı		
Conte	nt				C	ompeter	ncies						
Unit	1: Intr	oductio	on to N	Machin	e Lear	ning; I	ntroduc	ction to	Super	vised L	earning;		
Decisi	on Tre	es											
Overv	iew of	Super	vised	(regress	sion 1	. Gain	a basic	underst	anding	of differe	ent types		
and	classi	fication), un	supervi	sed	of pr	oblems	and n	omencla	ture in	machine		



	to be University under Section 3 of the UGC Act, 1936)
(clustering and dimensionality	
reduction), semi-supervised, and	2. Understand and interpret results of cross
reinforcement learning with practical	validation in machine learning through a
examples - Machine learning	simple algorithm (C2, C3).
nomenclature: raw data, types of	3. Understand the decision tree learning model
features and outputs, feature vector.	and splitting criteria (C2).
	4. Compare and contrast classification vs.
Computing distances and similarities -	regression using decision trees (C4).
Prototype based classification - K-	
nearest neighbors - 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	
Unit 2: Linear Models; Feature Selecti	on; Introduction to Unsupervised Learning
Linear model for regression and	1. Understand the basics of linear models for
classification - Simple linear	regression and classification, interpret results
regression: model, estimation and	and coefficients (C4).
interpretation of coefficients -	2. Differentiate feature selection approaches in
Introduction to bias/variance tradeoff -	machine learning (C4).
Regularized linear regression	3. Understand the working principle behind
	hierarchical clustering (C2).
Filter, wrapper, and embedded methods	4. Visualize the mathematical setup behind PCA
	and compare the matrix-factorization vs.
Clustering vs. classification -	projection-error-minimisation approaches (C4,
Hierarchical clustering: dendogram	C5).
construction, types of linkage -	
Dimension reduction using principal	
component analysis (PCA)	



Unit 3: Probabilistic Models for Su	upervised Learning; Support Vector Machine;
Ensemble Methods	
Probabilistic modeling of data using	1. Formulate maximum likelihood estimation of
parameters - Introduction to maximum	model parameters (C5).
likelihood estimation (MLE) of	2. Understand the probabilistic principles behind
parameters - Naive Bayes model for	Naive Bayes and Logistic Regression
classification - Logistic regression for	algorithms (C2).
binary classification	3. Formulate the SVM mathematical model and
	interpret algorithm parameters and results
Classification using linear SVM -	(C5).
Dealing with nonlinearly separable	4. Develop intuition and ideas behind ensemble
data	algorithms for machine learning (C5).
Bagging: classification using random	

forest - Boosting

Learning strategies, contact hours and student learning time

Learning strategy	Contact hours	Student learning
0 07		
		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 & V	iva		Viva	Viva					
Mapping of assessme	ent with Co	S							
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CO 5			
Sessional Examinatio	n 1	*	*						
Sessional Examinatio	n 2		*	*	*				
Assignment/Presentat	ion	*	*	*	*	*			
End Semester Examir	*	*	*	*	*				
Feedback Process	Mid-Semester feedback								
	• End-Semester Feedback								
Reference Material	1. Grokkii	ng Ma	chine	Learning,	Luis G.	Serrano, Manning			
	Publicatior	ns; 1st E	Edition, 2	2019.					
	Online r	esource	from	Mannir	ng Publicati	ons available at			
	https://ww	w.mann	ing.com	/books/gr	okking-machi	ine-learning			
	2. A Cour	se in M	achine I	Learning,	Hal Daumé I	II – Online resource			
	available a	t http://o	ciml.info)/					
	3. An Intr	oductio	on to Sta	atistical L	earning with	Applications in R,			
	Gareth Jan	nes, Da	niela Wi	tten, Trev	vor Hastie and	d Robert Tibshirani,			
	Springer; 1	st Editi	on, 2013	, Corr. 7t	h printing 201	7 Edition.			
	4. Mathen	natics f	or Mach	nine Lear	ning, Marc H	Peter Deisenroth, A			
	Aldo Faisa	l, and C	Cheng So	on Ong –	Online resou	rce from Cambridge			
	University	Press	available	e at https	://mml-book.g	github.io/book/mml-			
	book.pdf.								



Name	of the P	rogram	:		ME in	n Machine	Learnir	ıg				
Course	Title:				Appli	Applied Machine Learning Lab						
Course	Code:	MCL 60)5L		Cour	Course Instructor:						
Acade	nic Yea	nr: 2020-	-2021		Seme	ster: Firs	t Year, S	emester	1			
No of (Credits:	1			Prere	equisites:	MCL 60	5, Pytho	n progra	mming		
Synop	sis:	This c	ourse p	rovides	a cod	ing-based	l introd	uction t	o impor	tant conc	epts and	
		algorit	hms in a	applied	machi	ne learni	ng using	g Pythor	l .			
Cours	e											
Outco	mes	On suc	cessful	comple	etion of	f this cou	rse, stuc	lents wi	ll be abl	le to		
(COs)	:											
CO 1:		Develo	Develop codes using state of the art machine learning tools and libraries.									
CO 1		Code	differen	nt type	es of	machine	elearni	ng par	adigms	and ch	oose an	
CO 2: appropriate one for a g						applicatio	on probl	em.				
<u> </u>		Code	differer	nt type	s of a	supervise	d and	unsupe	rvised	machine	learning	
CO 3:	algorithms to practical problems and assess their performance.											
CO 4.		Implement and explore feature engineering approaches in machine learning										
CO 4:		applica	ations.									
		Acquir	e a soli	d found	lation	in coding	skills f	or more	advanc	ed applic	ations of	
CO 5:		machin	ne learn	ing.								
Mapp	ing of (COs to 2	POs									
COs	<i>PO 1</i>	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO 5	PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11	
CO 1	*		*	*	*							
CO 2	*	*	*	*	*							
CO 3	*	*	*	*	*	*		*				
CO 4		*	*	*	*	*				*		
CO 5	*	*	*	*	*				*			
Cours	e conte	ent and	outcom	es:						1		
Conter	ıt				(Competer	ıcies					
Unit 1	l: Intr	oductio	on to N	Aachin	e Lea	rning; I	ntrodu	ction to	Super	rvised L	earning;	
Decisi												
Overvi	ew of	Super	vised	(regress	sion 1	l. Progra	am da	ta, pe	rform	data w	rangling,	
and classification), unsupervised understand the data matrix, and differentiate												
(cluste	ring	and	dim	ensiona	lity	betwe	en samp	ole and f	eature (C2, C4).		



	to be University under Section 3 of the UGC Act, 1956)
reduction), semi-supervised, and	
reinforcement learning with practical	using the K-nearest neighbor algorithm (C3).
examples - Machine learning	3. Implement and interpret results of cross-
nomenclature: raw data, types of	validation (C3).
features and outputs, feature vector.	4. Implement decision tree models in Python,
	fine-tune model parameters, and interpret
Computing distances and similarities -	results (C4).
Prototype based classification - K-	
nearest neighbors - 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	
impunty - Dunding a decision tiec	
	ion; Introduction to Unsupervised Learning
Unit 2: Linear Models; Feature Select	ion; Introduction to Unsupervised Learning 1. Implement linear models in Python, and
Unit 2: Linear Models; Feature Select	1. Implement linear models in Python, and
Unit 2: Linear Models; Feature Select Linear model for regression and	1. Implement linear models in Python, and interpret model coefficients for practical
Unit 2: Linear Models; Feature SelectLinear model for regression andclassification - Simple linearregression: model, estimation and	1. Implement linear models in Python, and interpret model coefficients for practical
Unit 2: Linear Models; Feature SelectLinear model for regression andclassification - Simple linearregression: model, estimation and	1. Implement linear models in Python, and interpret model coefficients for practical problems.
Unit 2: Linear Models; Feature SelectLinear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients -	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff
Unit 2: Linear Models; Feature SelectLinear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance tradeoff -	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4).
Unit 2: Linear Models; Feature SelectLinear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance tradeoff -	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4). Compare, and contrast different feature
Unit 2: Linear Models; Feature Select Linear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance tradeoff - Regularized linear regression	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4). Compare, and contrast different feature engineering approaches for practical problems
Unit 2: Linear Models; Feature Select Linear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance tradeoff - Regularized linear regression	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4). Compare, and contrast different feature engineering approaches for practical problems (C4).
Unit 2: Linear Models; Feature Select Linear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance tradeoff - Regularized linear regression Filter, wrapper, and embedded methods	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4). Compare, and contrast different feature engineering approaches for practical problems (C4). Visualize the output of hierarchical clustering
Unit 2: Linear Models; Feature SelectLinear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance tradeoff - Regularized linear regressionFilter, wrapper, and embedded methodsClustering vs. classification -	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4). Compare, and contrast different feature engineering approaches for practical problems (C4). Visualize the output of hierarchical clustering and PCA algorithms, and interpret the results
Unit 2: Linear Models; Feature SelectLinear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance tradeoff - Regularized linear regressionFilter, wrapper, and embedded methodsClustering vs. classification - Hierarchical clustering: dendogram	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4). Compare, and contrast different feature engineering approaches for practical problems (C4). Visualize the output of hierarchical clustering and PCA algorithms, and interpret the results
Unit 2: Linear Models; Feature SelectLinear model for regression andclassification - Simple linearregression: model, estimation andinterpretation of coefficients -Introduction to bias/variance tradeoff -Regularized linear regressionFilter, wrapper, and embedded methodsClustering vs. classification -Hierarchical clustering: dendogramconstruction, types of linkage -Dimension reduction using principal	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4). Compare, and contrast different feature engineering approaches for practical problems (C4). Visualize the output of hierarchical clustering and PCA algorithms, and interpret the results
Unit 2: Linear Models; Feature SelectLinear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance tradeoff - Regularized linear regressionFilter, wrapper, and embedded methodsClustering vs. classification - Hierarchical clustering: dendogram construction, types of linkage -	 Implement linear models in Python, and interpret model coefficients for practical problems. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4). Compare, and contrast different feature engineering approaches for practical problems (C4). Visualize the output of hierarchical clustering and PCA algorithms, and interpret the results



Unit 3: Probabilistic Models for Supervised Learning; Support Vector Machine; Ensemble Methods

Probabilistic modeling of data using	1.	Implement maximum likelihood estimation for
parameters - Introduction to maximum		a simple model (C4).
likelihood estimation (MLE) of	2.	Analyze the performance of the Naive Bayes
parameters - Naive Bayes model for		model for practical problems (C4).
classification - Logistic regression for	3.	Apply the SVM algorithm for linearly- and
binary classification		not-linearly separable data, compare and
		contrast the performance (C5).
Classification using linear SVM -	4.	Through coding, understand how ensemble
Dealing with nonlinearly separable		methods in machine learning work (C3).
data		

Bagging: classification using random forest - Boosting

Learning strategies, contact hours and student learning time

	Student learning
	time (Hrs)
12	-
-	-
-	-
-	-
-	-
-	-
03	-
-	-
24	-
03	-
06	-
48	-
	- - - - 03 - 24 03 03 03 03



Formative:	Summative:						
Internal practical Test	Ī	Sessional examination					
Theory Assignments					End semester examination		
Lab Assignment & V	iva				Viva		
Mapping of assessme	ent with Co	S					
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CO 5	
Sessional Examinatio	n 1	*	*				
Sessional Examinatio	n 2			*	*		
Assignment/Presentat	ion	*	*	*	*	*	
Laboratory examinati	on	*	*	*	*	*	
Feedback Process Reference Material	 End 1. Grokki Publication Online r https://ww 2. A Cour available a 3. An Intr Gareth Jar Springer; 1 4. Mather Aldo Faisa 	d-Semes ng Ma ns; 1st E esource w.mann rse in M at http://d roductio nes, Da lst Editi natics f al, and C	Edition, 2 from ing.com lachine I ciml.info on to Sta niela Wi on, 2013 for Mach Cheng Sc	back Learning, 2019. Mannir /books/gro Learning, / atistical L atten, Trev 3, Corr. 7th nine Lear oon Ong –	earning with yor Hastie and h printing 201 ning, Marc 1 Online resou	ions available at ine-learning II – Online resource Applications in R, d Robert Tibshirani,	



Name	ne of the Program: ME						ME in Machine Learning					
Course Title: App						Applications of Graph Theory						
						Course Instructor:						
							ter: First	Year, S	emester	1		
No of	Credits	: 3			Pre	rec	quisites:	Discrete	mathem	atics		
Synop	sis:	This c	ourse p	rovides	an	intı	roductio	n to ba	sic grap	h theor	etic conc	epts and
		some a	some applications in machine learning.									
Cours	e											
Outco	mes	On suc	cessful	comple	etion	of	this cou	rse, stud	lents wi	ll be abl	e to	
(COs)	:			_								
<i>~~</i> 1		Develo	op a the	orough	unde	rst	anding o	of funda	amental	graph t	heoretic	concepts
CO 1:		and an	ply ther	n to und	derst	and	ling prac	tical pr	oblems			
CO 2:		-					• •	-			roblama	
				_					_		roblems .	
CO 3:		Relate	a real-l	ife prob	lem	to a	an appro	priate g	raph the	eoretic s	etup.	
CO 4:		Descri	be how	graph t	heor	y ca	an be us	ed for m	nachine	learning	g applicat	ions.
CO 5:		Compa	are and	contrast	t app	lica	ations of	graph t	heory to	o small a	and big da	ata.
Mapp	ing of (COs to	POs									
COs	<i>PO 1</i>	<i>PO 2</i>	<i>PO 3</i>	<i>PO</i> 4	PO	5	PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11
CO 1	*											
CO 2	*	*	*									
CO 3	*	*	*									
CO 4		*	*	*			*				*	
CO 5		*	*	*						*		
Cours	e conte	ent and	outcom	les:	1			I		1	1	<u> </u>
Conte	nt					Competencies						
Unit 1	: Grap	hs; Eul	er Tou	rs and]	Ham	ilto	on Cycle	es				
Graph	s and	their	represe	ntations	s -	1.	Under	stand ba	asic con	nponent	s of a gra	ph (C2).
Incide	nce an	nd adja	cency	matrice	s -	- 2. Understand, compare and contrast incidence					ncidence	
Vertex	degree	es - Pat	hs and	connect	tion		and ac	ljacency	matric	es (C2,	C5).	
- Cyc	les - Di	rected g	graphs -	Subgra	phs	3.	Under	stand t	he prac	tical ap	plication	s of the
and s	upergra	phs - '	The sho	ortest p	oath	h traveling salesman problem (C3).						
proble	m - Fo	prests a	nd trees	, Cayle	ey's							
formu	la.											



The traveling salesman problem.				
Unit 2: Flow in Networks; Matchings;	Coloring Problems	s		
Flows and cuts - Max-flow min-cut theorem and its applications.	applications (C			
Matchings and coverings in bipartite graphs - Perfect matchings - Applications of matchings.	practical applic 3. Understand ed practical applic	ge & vertex coloring and their		
Edge coloring & Vertex coloring.				
Unit 3: Random walks and Application	s; Spectral Cluste	ring and Applications		
	 Understand random walks and its practical applications (C3). Model multidimensional data as similariting graph (C4). Understand spectral clustering and its practical applications (C3). 			
Learning strategies, contact hours and	student learning t	ime		
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 semes	End semester examination					
Lab Assignment & Vi	Viva	Viva					
Mapping of assessme	ent with Co	DS					
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CO 5	
Sessional Examinatio	n 1	*	*				
Sessional Examinatio	n 2		*	*	*		
Assignment/Presentat	ion	*	*	*	*	*	
End Semester Examir	nation	*	*	*	*	*	
Feedback Process	• Mi	d-Seme	ster feed	back			
	• En	d-Semes	ster Feed	lback			
Reference Material	1. Introdu	ction to	Graph T	Theory, Ri	chard J. Trud	eau, Dover	
	Publica	tions In	c.; 2nd F	Revised E	dition, 1994.		
	2. Pearls	2. Pearls in Graph Theory: A Comprehensive Introduction, Nora					
	Hartsfi	Hartsfield and Gerhard Ringel, DoverPublications, 2003.					
	3. Graphy	Theory	, Adrian	Bondy, N	A. Ram Murt	y, Springer	
	Publica	tions,1s	t Editior	n, 2008.			



Name	of the P	rogram	:		ME in	ME in Machine Learning					
Course Title: App					Applic	Applications of Graph Theory Lab					
					• •	Course Instructor:					
Acade	nic Yea	r: 2020-	-2021		Semes	ster: First	Year, S	emester	1		
No of (Credits:	1			Prere	quisites: 1	MCL 61	5			
Synop	sis:	This c	ourse p	rovides	a prac	ctical intr	roductio	on to ur	nderstan	ding, vis	ualizing,
		and ap	plying t	oasic gra	aph the	oretic co	ncepts t	o practi	cal prob	olems.	
Cours	e										
Outco	mes	On suc	cessful	comple	tion of	this cour	se, stud	ents wil	ll be abl	e to	
(COs)	:										
CO 1:		Visual	ize grap	hs and	graph r	nodels us	sing Pyt	hon.			
CO 2:							_			cal proble	
CO 3:		Implen	nent gra	ph theo	retic a	proache	s for ma	achine le	earning	applicatio	ons.
Mapp	ing of (COs to 1	POs								
COs	PO 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11
CO 1	*										
CO 2	*	*	*		*						
CO 3	*	*	*		*						
Cours	e conte	nt and	outcom	es:							
Conter	ıt				0	Competencies					
Unit 1	: Grap	hs; Eul	er Tou	rs and l	Hamilt	on Cycle	s				
Graphs	and	their	represe	ntations	- 1	- 1. Visualize graphs using Python (C3).					
Incide	nce an	d adjao	cency r	natrices	. – 2						
Vertex	degree	es – Pat	hs and	connect	ion						
- 0	Cycles	– Dir	rected	graphs	-	(C3).					
Subgra	iphs a	nd sup	ergraph	ns — 7	Гhe						
shortes	st path	proble	m – F	orests a	and						
trees, Cayley's formula.											
The tra	veling	salesma	an probl	em.							
Unit 2	: Flow	in Netv	vorks; I	Matchi	ngs; Co	oloring P	roblem	IS			
Flows	and c	uts - N	Max-flo	w min-	cut 1	. Visual	ize ne	twork	flow p	roblems	through
theorem	n and i	ts applie	cations.			applica	ations (C3).			
						. Impler	nent pr	actical a	applicati	ions of n	natching,



(Deemed to Spire Dev Life)	to be University under Section 3 of a	the UGC Act, 1956)		
Matchings and coverings in bipartite	edge & vertex	coloring (C	3).	
graphs - Perfect matchings -				
Applications of matchings.				
Edge coloring & Vertex coloring.				
Unit 3: Random Walks and Applicatio	ns; Spectral Clust	tering and A	Applications	
	1. Create a ra	ndom wall	k and analyze its	
	properties (C4	4).		
	2. Model multi	dimensional	data as similarity	
	graph (C4).			
	3. Apply spectra	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:			<u> </u>	
Formative:		Summati	ve:	
Internal practical Test		Sessional examination		
Theory Assignments		End seme	ster examination	



Lab Assignment & Vi	iva	Viva							
Mapping of assessme	Mapping of assessment with Cos								
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CO 5			
Sessional Examinatio	n 1	*	*						
Sessional Examinatio	n 2			*	*				
Assignment/Presentat	ion	*	*	*	*	*			
Laboratory examination	on	*	*	*	*	*			
Feedback Process	• Mi	d-Seme	ster feed	back					
	• En	• End-Semester Feedback							
Reference Material	1. Introdu	ction to	Graph 7	Theory, Ri	chard J. Trud	leau, Dover			
	Publica	tions In	c.; 2nd F	Revised E	dition, 1994.				
	2. Pearls	2. Pearls in Graph Theory: A Comprehensive Introduction, Nora							
	Hartsfi	Hartsfield and Gerhard Ringel, DoverPublications,2003.							
	3. Graphy	Theory	, Adrian	Bondy, N	A. Ram Murty	y, Springer			
	Publica	tions,1s	t Editior	n, 2008.					



turningbasedmodellstrategiCourseOutcomes(COs):CO 1:ExtractUnders	2 2021 ourse provid ; data into r on data ava ing and data ic visual enco cessful comp	Prince Courses Semi- Prenes insigne eadable ilable a process oding ba	ciples o rse Instr ester: Fi equisite ght on graphi and tas ing; ma ased on	ructor: irst Year, s: Progra data vis ics; des ks to b p data a	Semester amming ir sualizatio ign and be achiev ttributes	1 n Python n, the an create da ved; data to graphi	ata visua extracti cal attribu	lizations on, data
Academic Year: 2020-No of Credits: 3Synopsis:This constrainedSynopsis:This constrainedbasedbasedbasedmodellingstrategiStrategiCourseOn succonstrained(COs):ExtractCO 1:Extract	2021 ourse provid ; data into r on data ava ing and data ic visual enco cessful comp	Courses Semi- Prer es insig readable ilable a process oding ba	rse Instr ester: Fi equisite ght on graphi and tas ing; ma	ructor: irst Year, s: Progra data vis ics; des ks to b p data a	, Semester amming ir sualizatio ign and be achiev ttributes	1 n Python n, the an create da ved; data to graphi	ata visua extracti cal attribu	lizations on, data
No of Credits: 3Synopsis:This constructionSynopsis:This constructionbasedbasedbasedmodellingstrategingStrategingCourseOn such(COs):On suchCO 1:ExtractUnderseUnderse	ourse provid data into r on data ava ing and data ic visual enco cessful comp	Prer es insig readable ailable a process oding ba	equisite ght on graphi and tas ing; ma ased on	s: Progra data vis cs; des ks to b p data a	amming ir sualizatio ign and be achiev ttributes	n Python n, the ar create da ved; data to graphi	ata visua extracti cal attribu	lizations on, data
Synopsis:This constructionSynopsis:This constructionturningbasedbasedmodellingstrategingStrategingCourseOn succonstruction(COs):On succonstructionCO1:ExtractionUnderseUnderse	data into r on data ava ing and data ic visual enco cessful comp	es insig eadable ilable a process oding ba	ght on graphi and tas ing; ma ased on	data vis ics; des ks to b p data a	sualizatio ign and be achiev ttributes	n, the ar create da ved; data to graphi	ata visua extracti cal attribu	lizations on, data
turning based modell strategi Course Outcomes (COs): CO 1: Extract Unders	data into r on data ava ing and data ic visual enco cessful comp	eadable ilable a process oding ba	graphi and tas ing; ma ased on	ics; des ks to b p data a	ign and he achiev ttributes	create da ved; data to graphi	ata visua extracti cal attribu	lizations on, data
CourseOn sucOutcomesOn suc(COs):ExtractCO 1:Extract	on data ava ing and data ic visual enco cessful comp , transform a	ilable aprocess	and tast ing; ma	ks to b p data a	e achiev ttributes	ved; data to graphi	extracti	on, data
modelli strategiCourseOn suc On suc (COs):CO1:Extract Unders	ing and data ic visual enco cessful comp , transform a	process oding ba	ing; ma used on	p data a	ttributes	to graphi	cal attrib	
CoursestrategiOutcomesOn suc(COs):ExtractCO 1:Extract	cessful comp	oding ba	used on	-				utes, and
Course On suc Outcomes On suc (COs): Extract CO 1: Extract	cessful comp			known j	propertie	s of visua		
OutcomesOn suc(COs):ExtractCO 1:ExtractUnders	, transform a	oletion o	of this co				al percept	ion.
(COs):CO 1:ExtractUnders	, transform a	oletion of	of this co					
CO1: Extract Unders				ourse, st	udents w	ill be abl	e to	
Unders								
		nd store	e data fr	om vari	ous data	sources.		
CO 2. data m	tand the key	y techni	ques a	nd theor	ry used i	n visuali	ization, i	ncluding
	data models, graphical perception and techniques for visual encoding and						ling and	
interact	interaction.							
CO 3: Work v	Work with a number of common data domains and corresponding analysis							
tasks.	tasks.							
CO 4: Build a	Build and evaluate visualization systems.							
CO 5: Read at	nd discuss re	search p	papers f	rom the	visualiza	ation liter	ature.	
Mapping of COs to I	POs							
COs PO 1 PO 2	<i>PO 3 PO 4</i>	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11
CO 1 *	*	*	*					
CO 2 * *		*						
CO 3 * *	*							
CO 4 *	*	*			*			
CO 5 * *	* *							
Course content and	outcomes:		•	•	•			<u>.</u>
Content			Compe	tencies				
Unit 1: Introduction	to Web Scr	aping						
Web scraping models	Web scraping models and techniques,					us forma	ts of data	. (C1)
Case study: Beauti	and techniqu		2. Des					



Selenium	from web. (C4)
	3. Design programs to read data from variou
	data sources. (C4)
Unit 2: Data Analysis	
	1 Understand and integrate versions do
Data structures for analysis: numpy,	1. Understand and integrate various dat
pandas	structures for data analysis process (C2).
Data Wrangling: Clean, Transform,	2. Create various techniques to clean and hand
Merge, Reshape	missing data (C4).
Data Aggregation and Group	3. Design data filtering and transformation
Operations	techniques (C4).
Case study: Exploratory analysis of	
public / scrapped datasets	
Unit 3: Data Visualization	
Data Visualization – classification,	1. Describe what is the purpose of Visualization
infographics versus data visualization,	(C2)
visualization for supporting exploratory	2. Describe various ways of classifyin
data analysis, visual art, choosing	visualization. (C2)
appropriate visual encodings, rules for	3. Explain what is explorative and explanative
visualization - Visualization	visualization. (C2)
techniques: time series, statistical	4. Differentiate data visualization and visual ar
distributions, maps - Data visualization	(C2)
for web	5. Create visualization for time series data. (C4)
	6. Create visualization for statistica
	distributions. (C4)
	7. Create visualization for maps, Hierarchica
	data and network data. (C4)
Learning strategies, contact hours and	student learning time
Learning strategy	Contact hours Student learnin
	time (Hrs)
Lecture	30 60
Quiz	02 04
<u></u>	



Small Group Discussion (SGE	02			02			
Self-directed learning (SDL)	-			04	04		
Problem Based Learning (PBI	L)	02			04	04	
Case Based Learning (CBL)		-			-		
Revision		02			-		
Assessment		06			-		
TOTAL		44			74		
Assessment Methods:							
Formative:				Summati	ve:		
Internal practical Test				Sessional	examina	tion	
Theory Assignments				End seme	ster exan	nination	
Lab Assignment & Viva				Viva			
Mapping of assessment with	Cos			1			
Nature of assessment	CO 1	CO 2	C	CO 4		CO 5	
			0				
			3				
Sessional Examination 1	*	*					
Sessional Examination 2			*	*			
Assignment/Presentation	*	*	*	*		*	
End Semester Examination	*	*	*	*		*	
Laboratory examination	*	*	*	*		*	
Feedback Process •	Mid-Semes	ster feedbac	k	I			
•	End-Semes	ster Feedbac	ck				
Reference Material 1. We	bsite Scra	ping with	Pyt	thon: Usin	ng Beau	tifulSoup and	
Scr	apy, Gábo	r &Hajba,	AF	PRESS Put	olications	s, 1 st Edition,	
201	8.						
2. We	b Scraping	g with Pyt	hon:	Collecting	g More	Data from the	
Мо	dern Web,	Ryan Mitc	hell S	Shroff, O'R	eilly, 2 nd	Edition, 2018.	
3. Des	signing Dat	ta Visualiz	atio	ns, Julie St	eele and	Noah Iliinsky;	



	O'Reilly Media; 1 st Edition, 2011.
4.	Python for Data Analysis, Wes McKinney; Shroff; O'Reilly; 2 nd
	Edition, 2018.



Name of the Program: ME					E in Machine Learning						
3					inciples of Data Visualization Lab						
					ourse Instructor:						
Academic Yea	ar: 2020-	2021		Sen	nest	er: Firs	t year, S	emester 1	1		
No of Credits:	: 1			Pre	ereq	uisites:	Program	nming in	Python		
Synopsis:	Thi	s cours	e provi	des i	insig	ght on	data vis	sualizatio	on, the a	art and sc	ience of
	turi	ning da	ta into 1	reada	able	graphi	cs; des	ign and	create d	ata visua	lizations
	based on data available and tasks to be achieved; data extraction, data							on, data			
	mo	delling	and dat	a pro	oces	ssing; n	nap data	a attribut	tes to gra	aphical at	tributes,
	and	l strate	gic vis	ual	enc	oding	based	on kno	wn proj	perties o	f visual
	per	ception									
Course											
Outcomes	On suc	cessful	comple	tion	of t	his cou	rse, stu	dents wi	ll be abl	e to	
(COs):											
CO 1:	Scrape	data fro	om diffe	erent	: dat	ta sourc	es.				
CO 2:	Clean, analyze, and transform data.										
CO 3:	Visuali	ze data	using d	liffer	rent	technic	jues, to	ols and c	harts.		
Mapping of	COs to I	POs									
COs PO 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO	5	PO 6	<i>PO</i> 7	<i>PO</i> 8	PO 9	PO 10	PO 11
CO 1 *	*	*		*					*	*	
CO 2 *	*	*		*		*		*	*	*	
CO 3 *	*	*	*	*		*		*		*	
Course conte	ent and	outcom	es:								
Content					Co	ompeter	ncies				
Unit 1: Data	Scrappi	ing									
Web scrappin	ig model	S			1.	Identify	y differ	ent types	of data	sources ((C2).
Installing an	d conf	iguring	tools	to	2.	Design	applica	ations to	scrap st	atic data ((C4).
handle differe	ent data t	types.			3.	Design	appli	cations	to ext	tract dat	a from
	dynamic web pages (C4).										
Unit 2: Data	Analysi	S									
Working wit	h packa	ages lil	ke num	py,	1.	Design	scripts	s to cle	an, han	dle missi	ing data
pandas, sklea	rn					(C4).					
Perform expl	oratory c	lata ana	lysis.		2.	Design	scripts	to apply	require	d transfor	rmations



	to cleaned d	lata (C4).		
Unit 3: Data Visualization				
Creating different types of	1. Develop ap	plications for	exploratory data	
Visualization.	visualizatio	n (C4).		
Creating different types of charts.	2. Develop scr	ipts to create st	tatic visualization	
	using variou	us visual encodin	gs (C4).	
	3. Create dynam	nic visualization	for web (C4).	
Learning strategies, contact hours an	d student learnin	ig time		
Learning strategy	Contact hour	s S	tudent learning	
		ti	ime (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 ex	amination	
Theory Assignments		End semeste	ester examination	
Lab Assignment & Viva		Viva		
Mapping of assessment with Cos				
Nature of assessmentCO 1	1 CO 2	CO	3	



Sessional Examinatio	on 1 *						
Sessional Examinatio	n 2		*	*			
Assignment/Presentat	ion	*	*	*			
End Semester Examin	nation	*	*	*			
Laboratory Examinati	on	*	*	*			
Feedback Process	• Mi	d-Semeste	er feedback				
	• End	d-Semeste	r Feedback				
Reference Material	1. Websi	te Scrapi	ing with Python: U	Using BeautifulSoup and			
	Scrapy	y, Gábor	&Hajba, APRESS	Publications, 1 st Edition,			
	2018.						
	2. Web S	Scraping	with Python: Collec	ting More Data from the			
	Moder	n Web , R	yan Mitchell Shroff,	O'Reilly, 2 nd Edition, 2018.			
	3. Design	Designing Data Visualizations, Julie Steele and Noah Iliinsky;					
	O'Reill	O'Reilly Media; 1 st Edition, 2011.					
	4. Pythor	Python for Data Analysis, Wes McKinney; Shroff; O'Reilly; 2 nd					
	Edition	n, 2018.					



Name of the Program: ME							AE in Machine Learning						
8						Architecture of Big Data Systems							
						Course Instructor:							
							ter: Fi	rst Year	, Semeste	er 1			
No of C	No of Credits: 3Prerequisites: Programming in Python, Java												
Synops	sis:	This C	ourse p	rovides	insig	ght	on con	cept of	big data	characte	eristics, b	atch and	
		lambda architecture; basic file systems in Big Data; concepts of Hadoop										Hadoop	
		framework, Spark framework and their internals; Map-reduce programming,											
		Spark	progran	nming;	diffe	ren	t layers	with us	se cases o	demonst	rations.		
Course	e												
Outco	mes	On suc	cessful	comple	tion	of	this cou	rse, stu	dents wi	ll be abl	e to		
(COs):	:												
CO 1:		Exami	ne the t	ype of c	lata i	n b	oig data.						
CO 2:		To design applications based with Hadoop framework.											
CO 3:		To design applications based with spark architecture.											
CO 4:		To bu	ild app	lication	s ba	sed	l on th	e Big	Data Ar	chitectu	re platfo	rms and	
00.11		analyse	e the res	sults bas	sed o	n t	he outco	ome of	the appli	cations	used.		
Mappi	ng of (COs to 1	POs										
COs	<i>PO 1</i>	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO	5	PO 6	<i>PO</i> 7	<i>PO</i> 8	<i>PO</i> 9	PO 10	PO 11	
CO 1	*	*	*				*						
CO 2	*	*	*		*			*			*		
CO 3	*	*	*		*			*			*		
CO 4	*	*	*		*		*	*			*		
Course	e conte	ent and	outcom	es:									
Conten							ompeter	ncies					
Unit 1	: Class	ifying F	Big Data	a Chara	acter	ist	ics						
Analys	is type	- real ti	me or l	oatched	for	1. Identify different types of Data							
	later analysis.						2. Id	entify]	processin	ig metho	odology		
	•	nethodol		-									
•		-hoc que	•	reporti	ng.								
	-	ey and si											
	n dema	ind, as	with so	cial me	edia								
data													



(Deemed to	
Continuous feed, real-time -	
weather data, transactional data	
Time series - time-based data	
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 Lamb	oda architecture
Append-only, immutable data	1. Understand Lambda architecture to handle
Batch layer	Big Data (C2).
Serving layer	2. Understand different layers in Lambda
Speed layer	Architecture (C2).
Case study: Druid - A Real-time	
Analytical Data Store	
Unit 3: Batch Layer, Serving Layer and	d Speed Layer
Choosing a storage solution for the	1. Develop applications to store data in
batch layer: Distributed file systems,	HDFS (C4).
Vertical partitioning.	2. Develop applications for batch processing
MapReduce: a paradigm for Big Data	using Map Reduce technique (C4).
computing.	3. Understand the need of serving layer (C2).
Performance metrics for the serving	4. Design application to store data for
layer	processing in serving layer (C4).
Requirements for a serving layer	5. Understand the need of Speed layer for
database	data processing (C2).
Computing real time views	
Storing real time views	
Challenges of incremental computation	
Asynchronous versus synchronous	
updates	



Unit 4: Spark: Alternatives to MapRed	uce			
Spark Architecture	1. Understand Spark	Architecture for data		
Spark Session	processing (C2).			
DataFrame	2. Design applications	using DataFrames and		
Transformations and Actions	RDDs (C4).			
Spark SQL				
Resilient Distributed Datasets				
(RDDs)				
Unit 5: Stream Processing using Spark				
Advantages and challenges of stream	1. Understand different	nt stream processing		
processing	techniques (C2).			
Stream Processing Design Points	2. Design applications	for handling real time		
Streaming APIs	data using Structure	d Streaming (C4).		
Structured Stream Processing				
Unit 6: Machine Learning using Spark				
High level M-Lib concepts1. Understanddifferentlibraries				
M-Lib in Action	packages for mach	ine 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:					Summati	ve:	
Internal practical Test					Sessional	examination	
Theory Assignments					End seme	ster examination	
Lab Assignment & Vi	va				Viva		
Mapping of assessme	ent with Co	S			-		
Nature of assessment		CO 1	CO 2	CO 3	CO 4		
Sessional Examination	n 1	*	*				
Sessional Examination	n 2		*	*			
Assignment/Presentati	ion				*		
End Semester Examin	ation	*	*	*	*		
Laboratory examination	on	*	*	*	*		
Feedback Process	• Mie	d-Semes	ster feed	back			
	• End	l-Semes	ster Feed	lback			
Reference Material	1. Big Da	ta: Prin	ciples a	nd best pr	actices of sc	alable real-time data	
	system	s - Nath	an Marz	and Jame	es Warren. M	anning Publisher.	
	2. Hadoop	p: The	Definitiv	ve Guide:	Storage and	Analysis at Internet	
	Scale –	Tom W	Vhite, O	Reilly Pu	blication 4 th	Edition.	
	3. Spark:	The De	finitive	Guide: Big	g Data Proce	ssing Made Simple –	
	Bill Ch	ambers	, MateiZ	aharia, O	Reilly Public	cation 1 st Edition.	
	4. <u>http://s</u>	tatic.dru	<u>iid.io/do</u>	<u>cs/druid.p</u>	<u>odf</u> ,		
	<u>http://d</u>	ruid.io/	<u>docs/0.8</u>	.0/design/	design.html		
	5. Big dat	a archit	ecture a	nd pattern	s - IBM deve	loperWorks.	
	http://w	www.ibr	n.com/d	eveloperw	<u>/orks/library/</u>	bd-archpatterns1/	
6. Big Data and Analytics -IBM of						developerWorks.	
	http://www.ibm.com/developerworks/analytics/						
7. <u>http://lambda-architecture.net/</u>							
	8. Apache	e HBase	- <u>http://</u>	hbase.apa	che.org/		
	9. Apache	e Spark	Streamin	ng - <u>https:</u>	//spark.apach	e.org/streaming/	
	10. MapRe	duce lib	orary - h	ttps://githu	ub.com/twitte	er/summingbird	



Name o	of the P	rogram	:		ME	E in Machine Learning						
Course Title: Arch					chitecture of Big Data Systems Lab							
Course Code: BDA 623L Con					Cou	ırse Instru	ctor:	-				
Acaden	nic Yea	r: 2020-	-2021		Sen	nester: Firs	st year, S	emester	1			
No of C	Credits:	1			Pre	requisites:	Program	nming in	Python,	Java		
Synops	sis:	This C	ourse p	rovides	insig	ght on con	cept of l	big data	characte	eristics, b	atch and	
		lambda	a archit	ecture;	basi	c file sys	tems in	Big Da	ata; con	cepts of	Hadoop	
		framework, Spark framework and their internals; Map-reduce programming,									amming,	
		Spark	progran	nming;	diffeı	rent layers	with us	e cases (demonst	rations.		
Course	e											
Outcor	nes	On suc	cessful	comple	tion	of this cou	irse, stu	dents wi	ll be abl	e to		
(COs):												
CO 1:		Install	and dev	velop ap	plica	tions usin	g Hadoo	op and it	s ecosys	stems.		
CO 2:		Build a	applicat	ions usi	ng Sj	park frame	e work.					
CO 3:		Build I	Machin	e Learni	ing n	nodels usin	ng Spark	ζ.				
Mappi	ng of (COs to 1	POs									
COs	PO 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO	5 PO 6	<i>PO</i> 7	<i>PO</i> 8	<i>PO</i> 9	PO 10	PO 11	
CO 1	*	*	*		*	*			*	*		
CO 2	*	*	*		*	*			*	*		
CO 3	*	*	*		*	*			*	*		
Course	e conte	ent and	outcon	ies:								
Conten	nt -					Compete	ncies					
Unit 1:	Hado	op Eco	system									
Installa	tion a	and cor	nfigurin	g Had	oop	1. Practic	e applic	ations in	n HDFS	and YAF	RN. (C3)	
ecosyst	tem					2. Practic	e applie	cations	using S	qoop, Hi	ve, PIG.	
						(C3)						
						3. Comp	ute prog	rams usi	ng Map	Reduce.	(C3)	
Unit 2: Spark Framework												
	Spark tool chain – RDD, DataFrame, 1						1. Develop applications using Spark DataFrame					
	tool cl	nain — I	RDD, I	DataFra	me,	1. Develo	op appli	cations	using S	Spark Da	taFrame	



	2.	Design real t	ime app	lications using Spark		
		Streaming (C4).				
Unit 3: Machine Learning using S	park					
MLIB	1.	Compute mach	ine learni	ng models using Spark.		
		(C3)				
Learning strategies, contact hours	and stu	dent 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:			Summa	ative:		
Internal practical Test			Session	al examination		
Theory Assignments			End ser	nester examination		
Lab Assignment & Viva			Viva			
Mapping of assessment with Cos						
Nature of assessment C	CO 1	CO 2		CO 3		
Sessional Examination 1 *						



Sessional Examinatio	n 2	* *					
Assignment/Presentat	ion	*	*	*			
End Semester Examin	ation	*	*	*			
Laboratory Examination	on	*	*	*			
Feedback Process	• M	id-Semester	feedback				
	• Er	nd-Semester	Feedback				
Reference Material	1. Bi	g Data: Prir	ciples and best practice	es of scalable real-time			
	da	ta systems	- Nathan Marz and Ja	mes Warren. Manning			
	Pu	blisher.					
	2. Ha	adoop: The	Definitive Guide: Sto	orage and Analysis at			
	In	ternet Scale -	- Tom White, O'Reilly	Publication 4th Edition.			
	3. Sp	ark: The D	Definitive Guide: Big I	Data Processing Made			
	Si	Simple – Bill Chambers, Matei Zaharia, O'Reilly Publication					
	1s	t Edition.					



Name	of the F	rogram	:		ME	ME in Machine Learning								
Course	Title:				Min	Mini Project - 1								
Course	e Code:	MCL 69	95		Cou	Course Instructor:								
Acade	nic Yea	ar: 2020	-2021		Sem	Semester: First Year, Semester 1								
No of (No of Credits: 4 P						s: Progran	nming in I	Python /	R				
Synop	sis:	Studen	its are e	expecte	d to s	elect a p	roblem in	n the area	a of the	ir interes	t and the			
		area of	their s	peciali	zation	that wo	uld requi	re an imj	plement	ation in l	nardware			
	/ software or both in a semester													
Cours	e													
Outco	mes	On suc	cessful	compl	etion of	of this co	ourse, stu	dents wil	ll be abl	le to				
(COs)	:													
CO	N 1	Apply the objectives of the project work and provide an adequate background												
		with a detailed literature survey												
CO		Breako	Breakdown the project into sub blocks with sufficient details to allow the											
CO 2 work to be reproduced						by an independent researcher								
CO		Compose hardware/software design, algorithms, flowchart, methodology, and												
CO	5	block diagram												
CO) 4	Evalua	te the r	esults										
CO) 5	Summ	arize th	e work	carrie	ed out								
Mappi	ing of	COs to 2	POs											
COs	PO 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11			
CO 1				*										
CO 2					*			*						
CO 3							*			*				
CO 4						*					*			
CO 5							*							
Cours	e conte	ent and	outcon	nes:										
Conter	Content Competencies													
Phase	1													
Proble	m i	dentific	ation,	sync	psis	At the e	nd of the	topic stu	ident sh	ould be a	ble to:			
submis	ssion,	status	submis	ssion,	mid	1. Identify the problem/specification (C1)								
evalua	tion.					2. Discuss the project (C2)								



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	3. Prepare the outline (C3)	
	4. Describe the status of the	e project (C2)
	5. Prepare a mid-term proje	ect presentation report
	(C3)	
	6. Prepare and present	mid-term project
	presentation slides (C3, C	C5)
	7. Develop project	implementation in
	hardware/software or bo	th in chosen platform
	(C5)	
Phase 2		
Status submission, final evaluation.	1. Prepare the progress repo	ort (C3)
	2. Prepare the final project	et presentation report
	(C3)	
	3. Prepare and present fina	l project presentation
	slides (C3, C5)	
	4. Modify and Develop	implementation in
	hardware/software or bo	th in chosen platform
	(C3, C5)	
	5. Justify the methods used	l and obtained results
	(C6)	
Learning strategies, contact hours an	d 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	-	-
l		



Revision		-		-				
Assessment		03			-			
TOTAL		51			09			
Assessment Methods	:							
Formative:				Summati	ve:			
Project Problem Select	tion			Mid-Term Presentation				
Synopsys review				Second status review				
First status review			Demo & Final Presentation					
Mapping of assessme	ent 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 ch	ject						



Name	of the P	rogram			ME i	ME in Machine Learning							
Course		- 8	-			Seminar - 1							
Course	Code:	MCL 69	7		Cour	Course Instructor:							
Academic Year: 2020 -2021						Semester: First Year, Semester 1							
No of C	Credits:	: 1						inication S					
Synop	sis:	1. To	select,	search	and lea	rn tech	nical liter	rature.					
		2. To	Identif	y a cur	rent and	d releva	nt resear	ch topic.					
		3. To	prepare	e a topi	c and d	leliver a	presenta	ation.					
		4. To	develo	p the sl	cill to v	vrite a te	echnical	report.					
		5. De	velop a	bility to	o work	in grou	ps to rev	iew and 1	modify t	echnical	content.		
Course	e												
Outco	mes	On suc	cessful	compl	etion o	f this co	ourse, stu	dents wil	ll be able	e to			
(COs):	:												
CO 1		Show	compo	etence	in id	entifyin	g relev	ant info	ormation	n, defini	ng and		
COT		explaining topics under discussion.											
CO 2		Show competence in working with a methodology, structuring their oral											
02	work, and synthesizing information.												
CO 3		Use ap	propria	te regi	sters a	nd voca	bulary, a	nd will o	demonst	rate com	mand of		
05		voice r	nodula	tion, vo	oice pro	jection,	and paci	ing.					
CO 4		Demor	strate	that the	ey have	have paid close attention to what others say and can							
CU 4		respon	d const	ructive	ly.	,							
		Develo	p pers	suasive	speec	h, pres	ent info	rmation	in a c	ompelling	g, well-		
co =		structured, and logical sequence, respond respectfully to opposing ideas,											
CO 5		show depth of knowledge of complex subjects, and develop their ability to											
		synthe	size, ev	aluate	and ref	lect on i	nformati	on.					
Mappi	ing of (COs to]	POs										
COs	<i>PO</i> 1	PO 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11		
CO 1	*							*	*		*		
CO 2	*							*	*		*		
CO 3	*							*	*		*		
CO 4	*							*	*		*		
CO 5	*							*	*		*		



Learning strategies,	contact hou	irs and st	udent lea	rning ti	me			
Learning strategy			Contact I	hours		Student learning		
						tim	ne (Hrs)	
Lecture			-			-		
Seminar			-			-		
Quiz			-			-		
Small Group Discussi	on (SGD)		14			-		
Self-directed learning	(SDL)		-			-		
Problem Based Learn	ing (PBL)		-			-		
Case Based Learning	(CBL)		-			-		
Clinic			-			-		
Practical		-		-				
Revision		-			-			
Assessment			-			-		
TOTAL			14			-		
Assessment Methods	s:							
Formative:					Summative:			
Seminar Topic Select	ion							
Synopsys review								
PPT Review								
Mapping of assessme	ent with Co	s						
Nature of assessment		CO 1	CO 2	CO 3	CO 4		CO 5	
Presentation	*	*	*	*		*		
Feedback Process	• Enc	l-Semeste	r Feedbaa	l :k	<u> </u>			
Reference Material	Particular to the chosen Seminar							



Name o	of the P	rogram	:		ME	E in Machine Learning						
Course	Title:	_			Adv	lvanced Applications of Probability and Statistics						
Course	Code:	MCL 60	2			Course Instructor:						
Acaden	nic Yea	ar: 2020-	2021		Sen	Semester: First Year, Semester 2						
No of Credits: 3 Pro						requisite	s: MCL	601, 603				
Synops	sis:	This co	ourse p	rovides	s an i	ntroducti	on to a	dvanced	applicati	ons of pi	robability	
		and sta	tistics f	for mul	tivari	ate and ti	me seri	es data.				
Course	e											
Outcor	nes	On suc	cessful	compl	etion	of this co	ourse, st	udents w	ill be ab	le to		
(COs):												
CO	1:	Compu	te and in	nterpret	descri	iptive stat	istics for	multivari	ate data			
CO	2:	perform	nance	Ũ		-		•	•		ess model	
СО	CO 3: Interpret the output of principal component analysis (PCA) applied to multivariate data for dimension reduction											
CO 4: Identify multivariate data appropriate technique											_	
CO 5: Understand the basics of time series modelling and apply to real-life problems									ms			
Mapping of COs to POs												
COs	<i>PO 1</i>	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO 5	5 PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11	
CO 1	*		*									
CO 2	*	*	*	*								
CO 3	*	*	*	*				*				
CO 4		*	*	*	*	*						
CO 5	*	*	*									
Course	e conte	ent and	outcon	nes:								
Conten	et					Compet	encies					
Unit 1:	Mult	ivariate	Distri	bution	5							
Mean	vec	tor, d	covaria	nce	and	1. Und	erstand	the org	ganisatio	n of mu	ıltivariate	
correlat	tion –	popula	tion vs	. samp	ole -		(C2).	ltimoniat-	non-1-	tion -	0.00001-	
The m	nultiva	riate G	aussian	— jo	oint-,				popula	uon and	l sample	
margin	al-,	and		conditi	onal	parameters (C4).						
distribu	itions.	Mahala	nobis d	istance	and					ms (C2, 0		
distributions, Mahalanobis distance and outliers - Properties of the multivariate					4. Compare parameter estimation using different probabilistic approaches (C4).							
Gaussia	an -	Param	neter	estima	tion:	prot	a01115t1		1105 (04			
maxim	um lik	elihood	estimat	tion (M	ILE)							



and maximum aposteriori estimation (MAP).

Unit 2: Linear and Logistic Regression

Unit 3: Principal Component Analysis; Cluster Analysis

	1 Understand the methematical foundation of
Geometric intuition of principal	1. Understand the mathematical foundation of
	principal component analysis (PCA) (C2).
components - Maximum variance	2. Perform and interpret the output of PCA
perspective – algebraic setup,	applied to multivariate data for dimension
eigenvectors and eigenvalues of sample	reduction (C6).
	3. Assess when PCA is applicable for clustering
correlation matrix - Interpretation and	multivariate data (C6).
application of principal components for	
application of principal components for	4. Compare and contrast methods for clustering
dimension reduction.	multivariate data with mixed data types (C6).
Dissimilarity measures for mixed data	
types - Partition around medoids	
(DAM) us K maana alaanithmaa	
(PAM) vs. K-means algorithms -	
Selecting the number of clusters.	



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 Contact hours Student Learning strategy learning time (Hrs) 30 Lecture 60 02 04 Quiz Small Group Discussion (SGD) 02 02 Self-directed learning (SDL) 04 -Problem Based Learning (PBL) 04 02 Case Based Learning (CBL) _ _ Revision 02 _ Assessment 06 _ TOTAL 74 44 **Assessment Methods:** Formative: Summative: Internal practical Test Sessional examination Theory Assignments End semester examination Viva Lab Assignment & Viva Mapping of assessment with Cos

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



Sessional Examination	n 1	*	*			
Sessional Examination	Sessional Examination 2				*	
Assignment/Presentat	ion	*	*	*	*	*
End Semester Examin	ation	*	*	*	*	*
Feedback Process			ster feedb ster Feedl			
Reference Material	Gareth Jam Springer; 1 2. An Intr Everitt and 3. Machine Murphy, Th 4. Mathem Aldo Faisa 2020. – Or	nes, Dan st Edition oduction Torsten e Lear he MIT hatics for al, and aline res	niela Wit on, 2013, n to App n Hothorn ning - Press; 1s or Mach Cheng S source fr	ten, Trevo Corr. 7th olied Mult n– Springe A Probal st Edition, ine Learn Soon Ong om Camb	earning with App or Hastie and Ro printing 2017 Eo ivariate Analysis er Publications,1s bilistic Perspect 2012. ing, Marc Peter g, Cambridge U ridge University ml-book.pdf	bbert Tibshirani, dition. s with R, Brian st Edition, 2011. tive, Kevin P. Deisenroth, A niversity Press,



Name of	the P	rogram	:		ME	ME in Machine Learning							
Course T	itle:				Advanced Applications of Probability and Statistics Lab								
Course C	Code:	MCL 60	2L		Course Instructor:								
Academic			2021			ester: Fir			2				
	No of Credits: 1					requisites							
Synopsis	5:	This co	ourse p	rovides	an in	troductio	n to adv	vanced a	pplicati	ons of pr	obability		
		and sta	atistics	for ana	alysin	ıg multiv	ariate a	nd time	series	data usin	ig the R		
programming language.													
Course													
Outcome	es	On suc	cessful	comple	etion of	of this co	urse, stu	dents wi	ll be abl	e to			
(COs):													
CO 1:		Compute and interpret descriptive statistics for multivariate data											
CO 2: Build and assess linear and logistic regression models for practical problems								oblems					
CO 2:		Perform	n princ	cipal co	ompor	nent ana	ysis (P	CA) for	dimens	sion redu	ction in		
CO 3: multivariate data													
CO 4: Cluster multivariate da						ata with mixed data types							
CO 5:		Apply	time se	ries mo	dellin	g to real-	life proł	olems					
Mapping	g of (COs to 1	POs										
COs F	PO 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO :	5 PO 6	<i>PO</i> 7	<i>PO</i> 8	<i>PO</i> 9	PO 10	PO 11		
CO 1 *	k	*	*		*								
CO 2		*	*	*	*			*					
CO 3		*	*	*	*			*					
CO 4		*	*	*	*	*		*					
CO 5 *	k	*	*										
Course c	conte	nt and	outcom	es:			1		•	1	-		
Content						Compete	ncies						
Unit 1: N	Multi	variate	Distril	outions									
Mean	vect	or, c	covaria	nce	and	1. Com	pute de	scriptive	statistic	cs of mu	ltivariate		
correlatio	on –	popula	tion vs	. sampl	le -	data	(C2).						
The mu	ltivar	iate G	aussian	– joi	nt-,	2. Perfo	orm e	xplorator	ry dat	a analy	ysis of		
marginal	-,	and	(conditio	onal	mult	variate	data (C4).				
distributi	ions,	Mahala	nobis di	stance	and	3. Ident	ify outli	ers in m	ultivaria	ite data (O	C3).		
outliers -	- Prop	perties of	of the m	nultivar	iate	4. Visu	alise ar	nd under	rstand t	the prop	erties of		



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



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trend, seasonality, autocorrelation -	and asses	and assess performance (C3).			
Autoregressive moving average	2. Understand and apply in-built functions in				
(ARMA) models - Resampling,	R for time series modelling (C3).				
smoothing, windowing, and rolling	3. Apply time series modelling to practical				
average - First and second order	problems (C3).				
differencing - Validating time series	4. Interpret the results of times series model				
predictions.	predictions (C3).				
Learning strategies, contact hours and	student learning	g 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:	Formative:				
Internal practical Test	Sessional	Sessional examination			
Theory Assignments		End semester examination			
Lab Assignment & Viva		Viva			
Mapping of assessment with Cos		1			
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							



Name of the Program: ME					ME in Machine Learning							
Course	Title:				Mac	Machine Learning Principles & Applications						
Course	Code:	MCL 60	94			Course Instructor:						
Academic Year: 2020-2021 Sem					Semester: First Year, Semester 2							
No of Credits: 3 Pre					requisites	: MCL	601, 603, 6	505				
Synopsis: This course provides an a					dvanced	treatme	ent of ma	chine le	arning al	gorithms		
and the underlying mather								for careful	l selectio	on and an	alysis of	
algorithms for practical ap						plications	5.					
Course	e											
Outcon	mes	On suc	cessful	compl	etion	of this co	urse, st	udents wi	ll be abl	e to		
(COs):												
СО	1:	librarie	s.	-				the art n		-		
CO		machin	e learni	ng.				enerative			upervised	
CO	3:				-	-		racy and p				
CO	4:	techniq	ues to re	eal-life	proble	aling with practical difficulties in applying machine learning oblems.						
CO	5:	Develog features	-	dimensi	onal n	al models of application problems with mixed data type						
Mappi	ng of (COs to]	POs									
COs	<i>PO 1</i>	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11	
CO 1	*		*		*							
CO 2	*	*		*								
CO 3	*	*	*	*	*							
CO 4		*	*	*	*	*		*				
CO 5		*	*	*		*						
Course	e conte	ent and	outcon	ies:								
Conten	nt –					Compete	encies					
Unit 1	: Kern	el Meth	ods; L	inear I	Regre	ssion						
Kernel	s as t	feature	maps	- Ke	ernel	1. Und	erstand	the rela	tionship	betwee	n kernel	
functio	ns: ty	ypes, h	yperpa	rameter	:s -	func	tions ar	nd feature	mappin	g (C2).		
Kernel	mat	rix: in	terpret	ation	and	2. Und	erstand	how to a	develop	nonlinea	r models	
properties - Kernel (nonlinear) SVM.					1.	from linear ones using kernels (C2, C5).					5).	
						3. Construct the cost function for least mean						
Least mean squares (LMS) algorithm:					squares algorithm and apply gradient descent							



cost function - Gradient descent		(C5).				
algorithm: learning rate, batch and 4. Compare probabilistic interpretation of linear						
stochastic gradient approaches - regression with linear algebra based						
Probabilistic interpretation of linear		interpretation (C6).				
regression: MLE and MAP estimates.						

Unit 2: Generative Learning Algorithms; Regularization, Model Selection, & Evaluation

Gaussian discriminant analysis (GDA)	1. Model data flexibly by specifying a proper
- Naive Bayes algorithm: MLE	probabilistic model (C4).
estimates, Laplace smoothing.	2. Develop an optimization view of machine
	learning through MLE estimates (C5).
Grid search for best hyperparameters -	3. Undrestand how to efficiently identify optimal
Cross validation: types and practical	values of hyperparameters using grid search
approaches - Feature selection:	(C2, C3).
forward/backward search, wrapper	4. Choose appropriate feature engineering
model & filter feature selection -	approaches and quantitatively compare
Metrics for evaluating supervised &	machine learning algorithms (C6).
unsupervised machine learning	
algorithms.	

Unit 3: Imbalanced Data; Expectation Maximization; Dimension Reduction; Independent Component Analysis

Modifying the training data: over- and	1. Compare different approaches for dealing with
under-sampling - Modifying the loss	missing data (C6).
function.	2. Relate the EM framework for clustering with
	K-means clustering.
Clustering with a mixture of Gaussians	3. Construct and interpret low dimensional
- Expectation maximization (EM)	models of data (C5).
framework.	
	4. Develop models for analyzing mixed datatype
Factor analysis (FA) - Generalized low	data (C5).
rank models (GLRM).	



Independent Component	Analysis						
(ICA)							
Learning strategies, contact	hours and	student	learning	time			
Learning strategy		Conta	ct hours		Student learning		
					time (Hrs)		
Lecture		30			60		
Quiz		02			04		
Small Group Discussion (SGI))	02			02		
Self-directed learning (SDL)		-			04		
Problem Based Learning (PBI	L)	02			04		
Case Based Learning (CBL)		-			-		
Revision		02			-		
Assessment		06			-		
TOTAL		44			74		
Assessment Methods:							
Formative:				Summati	ve:		
Internal practical Test				examination			
Theory Assignments				ester 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-Semes	ster feed	back				
	End-Semes						
Reference Material 1 A C							
1. A C	Course in M	Iachine I	Learning,	Hal Daumé	III – Online resource		



	$P_{IRED BY}$ (Deemed to be University under Section 3 of the UGC Act, 1956)
	available at <u>http://ciml.info/</u>
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 o	rogram	:		ME in	ME in Machine Learning							
Course		0			Mach	Machine Learning Principles and Applications Lab						
		MCL 60)4L			Course Instructor:						
Academic Year: 2020-2021 Se				Seme	ster: Fin	rst Year,	, Semester	2				
No of Credits: 1 Pr				Prere	equisites	: MCL	604					
Synopsis: This course provides a				s a prac	ctical in	troduct	ion to a	dvanced	machine	learning		
		algorithms with an emphasis on careful analysis and selection of algorithms										
		for pra	ctical p	oroblem	IS.							
Course												
Outcor	nes	On suc	cessfu	l compl	etion of	f this co	ourse, st	udents w	ill be abl	e to		
(COs):												
CO 1:		Practic	ally ap	ply stat	e of the	e art ma	chine le	earning to	ols and l	libraries.		
co 2.		Implen	nent a	nd com	pare di	iscrimin	ative a	nd gener	ative su	pervised	machine	
CO 2:		learnin	g algo	rithms f	for prac	tical pro	oblems.					
00.0		Evalua	te ma	chine l	earning	algori	thms for	or accura	acy and	perform	ance for	
CO 3:		practical problems.										
00.4		Implement different strategies for selecting features and dealing with missing										
CO 4:		data.										
		Implement machine learning models for real-life data with mixed datatype										
CO 5:		feature		lacinite	learnin	saming models for fear me data with mixed datatype						
Mappi	ng of (COs to]	POs									
COs	<i>PO</i> 1	<i>PO</i> 2	PO	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11	
			3									
CO 1			*		*							
CO 2		*	*	*	*							
CO 3		*	*	*	*			*				
CO 4		*	*	*	*							
CO 5		*	*	*	*	*				*		
Course	e conte	nt and	outcor	nes:		•	•	•		·	· •	
Conten	at				(Compet	encies					
Unit 1:	Kern	el Meth	ods; L	inear I	Regress	sion						
Kernels	s as f	eature	maps	- Ke	ernel 1	l. Imp	lement	and com	pare dif	ferent ke	rnels for	
functio	ns: ty	vpes, h	yperpa	rameter	rs -	featu	ire map	ping (C4).			
Kernel	mat	rix: in	iterpret	ation	and 2	2. Imp	lement	kernel S	SVM an	d investi	gate the	



properties - Kernel (nonlinear) SVM.	effects of model parameters through
	visualization (C4).
Least mean squares (LMS) algorithm:	3. Implement gradient descent for least mean
cost function - Gradient descent	squares algorithm and investigate the effects of
algorithm: learning rate, batch and	hyperparameters on performance (C4).
stochastic gradient approaches -	4. Compare linear regression applied to practical
Probabilistic interpretation of linear	problems with and without regularization
regression: MLE and MAP estimates.	(C4).
Unit 2: Generative Learning Alg	orithms; Regularization, Model Selection, &
Evaluation	
Gaussian discriminant analysis (GDA)	1. Implement probabilistic models of data (C4).
- Naive Bayes algorithm: MLE	2. Perform grid search to identify best model
estimates, Laplace smoothing.	hyperparameters (C3).
estimates, Laplace smoothing.	nyperparameters (C3).
estimates, Laplace smoothing.	3. Perform feature engineering for real-life
Grid search for best hyperparameters -	
	3. Perform feature engineering for real-life
Grid search for best hyperparameters -	 Perform feature engineering for real-life problems (C3).
Grid search for best hyperparameters - Cross validation: types and practical	 Perform feature engineering for real-life problems (C3). Evaluate machine learning algorithms using
Grid search for best hyperparameters - Cross validation: types and practical approaches - Feature selection:	 Perform feature engineering for real-life problems (C3). Evaluate machine learning algorithms using
Grid search for best hyperparameters - Cross validation: types and practical approaches - Feature selection: forward/backward search, wrapper	 Perform feature engineering for real-life problems (C3). Evaluate machine learning algorithms using
Grid search for best hyperparameters - Cross validation: types and practical approaches - Feature selection: forward/backward search, wrapper model & filter feature selection -	 Perform feature engineering for real-life problems (C3). Evaluate machine learning algorithms using

Unit 3: Imbalanced Data; Expectation Maximization; Dimension Reduction; Independent Component Analysis

Modifying the training data: over- and	1.	Implement and compare different approaches
under-sampling - Modifying the loss		for dealing with missing data in real-life
function.		problems (C6).
~	2.	Implement and interpret low dimensional
Clustering with a mixture of Gaussians		models of data (C4).
- Expectation maximization (EM)	3.	Implement models for analyzing mixed



framework.	datatype data (C4).					
Factor analysis (FA) - Generalized low	4. Compare and contrast different techniques for					
rank models (GLRM).	dimension reduction and their practical					
	implications (C6).					
Independent Component Analysis						
(ICA)						

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	48		
Assessment Methods:				
Formative:		Summati		
Internal practical Test		Sessiona		
Theory Assignments		End seme	nd semester examination	
Lab Assignment & 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/Presentat	*	*	*	*	*					
Laboratory examination	on	*	*	*	*	*				
Feedback Process	Mid-Semester feedback									
	• End-Semester Feedback									
Reference Material	1. A Course in Machine Learning, Hal Daumé III – Online resource									
	available at <u>http://ciml.info/</u>									
	2. Macl	nine Lear	ming: A	Probabilis	stic Perspectiv	ve, Kevin Murphy, MIT				
	Pres	s,2017.								
	3. An I	ntroductio	on to Sta	tistical Le	arning with A	Applications in R, Gareth				
	Jame	es, Danie	la Witten	, Trevor I	Hastie and Ro	bert Tibshirani, Springer				
	Publ	ications,	2017.							
	4. Lectu	ire slides	of Prof.	Andrew	Ng – Stanford	d University – Available				
	onlir	e at http:	//cs229.s	tanford.ed	u/syllabus.htm	ป				
	5. Math	ematics	for Mach	nine Learr	ning, Marc Pe	eter Deisenroth, A Aldo				
	Fais	al, and (Cheng S	oon Ong	– Online re	source from Cambridge				
	Univ	ersity P	ress ava	ilable at	https://mml-b	oook.github.io/book/mml				
	book.pdf									
	6. Pattern Recognition and Machine Learning, Christopher Bis									
	Sprin	nger Publ	ications,	2017.						



Name of the Program: ME					AE in Machine Learning							
Course Title: Dee				p l	Learnin	g						
Course Code: MCL 606 Cou					Course Instructor:							
Acaden	Academic Year: 2020-2021 Semester: First Year, Semester 2											
No of C	redits:	: 3			Pre	ree	quisites	: MCL	601, 603, 6	505		
Synops	sis:	This co	ourse p	rovides	a thr	ou	igh con	nputatio	onal found	dation to	o the prin	ciples of
		deep le	arning	and its	appli	ca	tions.					
Course	ć											
Outcor	nes	On suc	cessful	compl	etion	of	this co	urse, st	udents wi	ll be abl	le to	
(COs):				Ĩ								
CO	1:	Gain a	solid un	derstan	ding o	f tl	he math	ematica	l basis of r	eural net	tworks.	
CO	2:	Develo	p practio	cal expe	rience	e w	vith state	of the a	art deep le	arning to	ols and lib	oraries.
CO	3:	Build a	nd analy	yze deep	o learn	ning	g model	s for ap	plication p	roblems.		
CO	4:	Devise	techniq	ues for i	impro	vin	g the w	ay neura	al network	s learn.		
СО	5:		•		•		•	•	earning mo			
Mappi	ng of (COs to 1							0			
COs	PO 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO 5	5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11
CO 1	*	*										
CO 2	*	*	*		*							
CO 3		*	*	*	*							
CO 4		*	*	*	*				*			
CO 5		*	*	*	*		*			*		
Course	e conte	ent and	outcon	nes:					•	•		<u> </u>
Conten	et					Competencies						
Unit 1:	Intro	duction	to Dee	ep Leai	rning	; N	Aatrix	Calcul	us; Logis	tic Regi	ression	
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					 Understand the basic architecture of a sigmoid neuron (C2). Reconstruct derivatives of multivariable functions using ideas from single variable calculus and linear algebra (C5). Develop intuition behind the gradient descent method (C5). Formulate the cost function for binary 							
descent		ethod–	intui		and	classification using logistic regression using						



	to be University under Section 3 of the UGC Act, 1936)
principle.	vectorized approach (C5).
Binary classification using logistic	
regression: cost function, gradient	
descent, and vectorization.	
Unit 2: Shallow Neural Network	
One hidden layer neural network:	5. Develop intuition for nonlinear activation
architecture and notation - The role of	functions (C5).
activation functions and their	6. Formulate backpropagation using matrix-
derivatives - Forward propagation	based approach (C5).
using matrix-based approach -	7. Develop intuition for and formulate loss
Cost/loss function: intuition and setup -	functions in deep learning (C5).
Gradient descent: backpropagation	8. Understand the importance of random
intuition and vectorized setup using	initialization of network parameters (C2).
matrix-based approach - Random	
initialization of network parameters.	
Unit 3: Deep Neural Network; Improv	ving the Way neural Networks Learn
Deep L-layer neural network:	1. Extend ideas from shallow neural network to a
architecture, notation, and building	deep neural network (C2).
blocks - Forward and backward	2. Formulate forward and backward propagation
propagation in a deep neural network	for a deep neural network using matrix-based
using matrix-based approach - The	approach (C5).
importance of deep representations -	3. Compare and contrast parameters and
Parameters vs. hyperparameters.	hyperparameters (C6).
The cross-entropy cost function - The	4. Gain an intuitive understanding of overfitting
learning slowdown problem -	and the use of regularization using different
Overfitting and regularization: L1/L2,	approaches (C2).
dropout - Weight initialization.	

Unit 4: Hyperparameter Tuning; Recurrent Neural Networks

Random initialization using appropriate	5.	Understand how to tune hyperparameters (C2).
• • • •		Intuitively understand the architecture of a



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

scales - Batch normalization.	recurrent neural network (C2).				
Recurrent neural network: architecture	7. Compare and contrast feed forward and				
and notation - Forward and backward	recurrent neural networks (C6).				
propagation through time - Different	8. Understand how to perform forward and				
types of recurrent neural networks and	backward propagation for recurrent neural				
their applications.	networks.				

Learning strategies, contact h	ours and	student	learning	time				
Learning strategy	Conta	ct hours	Student learning time (Hrs)					
Lecture		30			60	(11.0)		
Quiz		02			04			
Small Group Discussion (SGD)	1	02			02			
Self-directed learning (SDL)		-			04			
Problem Based Learning (PBL)		02			04			
Case Based Learning (CBL)		-			-			
Revision		02			-			
Assessment		06			-			
TOTAL		44	44			74		
Assessment Methods:								
Formative:				Summati	tive:			
Internal practical Test			Sessiona			al examination		
Theory Assignments			End sem			nester 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 feedbackEnd-Semester Feedback
Reference Material	 Neural Networks and Deep Learning, Michael Nielsen – Determination Press – Available online at http://neuralnetworksanddeeplearning.com/index.html Lecture slides of Prof. Andrew Ng – Stanford University – Available online at https://cs230.stanford.edu/syllabus/ Deep Learning, Ian Goodfellow, Yoshua Bengio, and Aaron Courville – MIT Press – Available online at http://www.deeplearningbook.org/



Name of the Program: ME					IE in Machine Learning							
Course Title: Dee					eep Learning Lab							
Course Code: MCL 606L Cou					Course Instructor:							
Acaden	Academic Year: 2020-2021 Sen					nest	ter: Fir	st Year,	Semester	2		
No of C	o of Credits: 1 Prerequisites: MCL 606											
Synops	sis:	This course provides a practical foundation to implementing deep learning										learning
		algorithms for real-life problems using state of the art software.										
Course	e											
Outcor	mes	On suc	cessful	compl	etion	of	this co	urse, st	udents wi	ill be abl	e to	
(COs):	:	On successful completion of this course, students will be able to										
CO 1:			-		-				s through I	-	-	-
CO 2:		Develo	p practi	cal expe	rience	e wi	ith state	e of the a	art deep le	arning to	ols and lib	oraries.
CO 3:		Implem	nent dee	p learni	ng mo	del	s for ap	plicatio	n problem	s.		
CO 4:		Implen	nent tech	nniques	for im	npro	oving th	e way n	eural netw	vorks lear	n.	
CO 5:		Numer	ically ar	nalyse d	eep le	arni	ing moo	dels and	select the	best mod	lel.	
Mappi	ng of (COs to	POs									
COs	PO 1	<i>PO</i> 2	PO 3	<i>PO</i> 4	PO :	5	PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11
CO 1	*				*							
CO 2		*	*		*							
CO 3		*	*	*	*							
CO 4		*	*	*	*							
CO 5		*	*	*	*		*		*			
Course	e conte	ent and	outcon	nes:	I							
Conten	nt and a second s					C	ompete	encies				
Unit 1:	: Intro	duction	to Dee	ep Leai	ning	; M	latrix	Calcul	us; Logis	tic Regi	ession	
Sigmoi	id neur	rons - T	The arcl	hitectur	e of	1.	Impl	ement	a sigmo	oid neur	on from	scratch
neural	networ	·ks.				(C3).						
Derivat	tives	in or	ne dir	nensior	1 -	2. Implement forward and backward propagation						
Deriva	tive i	n mul	tiple d	limensi	ons:		for a	sigmoi	d neuron	(C3).		
Derivative in multiple dimensions: gradient and Jacobian matrices - Rules					3.	Impl	ement	gradient	descen	t for a	sigmoid	
of matrix calculus: product and chain					neuron $(C3)$							
						4.	Impl	ement	cost	functio	n for	binary



^(Deemed) (Deemed)	to be University under Section 3 of the UGC Act, 1956)
rules - Optimizing using the gradient	classification using logistic regression using
descent method- intuition and	vectorized approach (C3).
principle.	
Binary classification using logistic	
regression: cost function, gradient	
descent, and vectorization.	
Unit 2: Shallow Neural Network	
One hidden layer neural network:	1. Visualize different nonlinear activation
architecture and notation - The role of	functions (C3).
activation functions and their	2. Implement forward and backward propagation
derivatives - Forward propagation	for a shallow neural network using matrix-
using matrix-based approach -	based approach (C3).
Cost/loss function: intuition and setup -	3. Implement gradient descent method for a
Gradient descent: backpropagation	shallow neural network (C3).
intuition and vectorized setup using	4. Numerically investigate the effect of random
matrix-based approach - Random	initialization of network parameters (C4).
initialization of network parameters.	
Unit 3: Deep Neural Network; Improv	ing the Way neural Networks Learn
Deep L-layer neural network:	1. Visualise architecture of a deep neural network
Deep L-layer neural network: architecture, notation, and building	(C3).
blocks - Forward and backward	2. Implement forward and backward propagation
propagation in a deep neural network	for a deep neural network using matrix-based
using matrix-based approach - The	approach (C3).
importance of deep representations -	3. Implement deep neural networks using in-built
	libraries for real-life problems (C4).
Parameters vs. hyperparameters.	4. Implement different regularization approaches
The cross-entropy cost function - The	and compare their advantages and
learning slowdown problem -	disadvantages (C6).
Overfitting and regularization: L1/L2,	
dropout - Weight initialization.	

Unit 4: Hyperparameter Tuning; Recurrent Neural Networks



Random initialization using appropriate	1.	Fine tune hyperparameters (C3).
scales - Batch normalization.	2.	Numerically investigate the effect of random
Recurrent neural network: architecture		initialization in deep neural networks (C4).
and notation - Forward and backward	3.	Visualise the architecture of a recurrent neural
propagation through time - Different		network (C3).
types of recurrent neural networks and	4.	Implement recurrent neural network models
¥ 1		for real-life problems.
their applications.		

Learning strategies, contact hours and student learning time

Learning strategy	Conta	ct 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	Clinic					-		
Practical	Practical					-		
Revision		03			-			
Assessment		06		-				
TOTAL		48			-			
Assessment Methods:								
Formative:				Summat	ive:			
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 Examinatio	n 1	*	*					
Sessional Examination 2**						*		
Assignment/Presentat	ion	*	*	*	*	*		
Laboratory examinati	*	*	*	*	*			
Feedback Process	• Mi	d-Seme	ster feedl	back				
	• End-Semester Feedback							
Reference Material	1. Neural Networks and Deep Learning, Michael Nielsen – Determination							
	Press – Available online at							
	http://ne	euralnet	worksando	leeplearning	g.com/index.html			
	2. Lecture	slides of	of Prof. A	ndrew Ng	- Stanford Unive	rsity – Available		
	online at https://cs230.stanford.edu/syllabus/							
	3. Deep Learning, Ian Goodfellow, Yoshua Bengio, and Aaron Courville –							
	MIT Pr	ess – Av	ailable on	line at http:	//www.deeplearni	ngbook.org/		



Name o	of the H	Program	:		ME	ME in Machine Learning								
Course	Title:					Reinforcement Learning								
Course	Code:	MCL 60)8		Cou	Course Instructor:								
Acaden	nic Yea	ar: 2020	-2021		Sen	Semester: First Year, Semester 2								
No of C	Credits	: 3			Pre	requisites	: MCL	601, 603						
Synop	sis:	This c	ourse pi	rovides	a tho	rough co	nputati	onal four	ndation t	o the prin	nciples of			
		reinfor	cement	learnii	ng and	d its appli	cations	•						
Course	e													
Outco	mes	On suc	cessful	compl	etion	of this co	urse, st	udents w	ill be abl	le to				
(COs):	:													
CO	1:		the key eractive				ent lear	ning that	distinguis	shes it fro	m AI and			
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												
CO	CO 4: Understand and implement commonly used reinforcement learning algorithms.													
CO	CO 5: Analyze algorithms for reinforcement learning.													
Mapping of COs to POs														
COs	<i>PO 1</i>	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO 5	5 PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11			
CO 1	*													
CO 2	*	*	-											
CO 3		*	*	*										
CO 4		*	*	*	*									
CO 5		*	*	*	*	*								
Course	e conte	ent and	outcon	nes:					•					
Conten	nt					Compete	encies							
Unit 1	: Intro	duction	to the	Reinfo	orcen	nent Lear	ning P	roblem;	Reinfor	cement]	Learning			
Frame	work;	Dynan	nic Prog	gramm	ing									
Examp	les	and	elem	ents	of	1. Gain	an	intuit	ive ur	nderstand	ing of			
reinforcement learning - Limitations reinforcement learning, related terminology,														
and sc	ope of	reinfor	cement	learni	ng -	and	contras	st it with	n other	machine	learning			
History of reinforcement learning.algorithms such as deep learning (C2, C6).														
						2. Dem	onstrat	e the	expl	oration	versus			
n-Armed bandit problem: action-value						expl	oitation	dilem	na usin	ig the	n-Armed			



⁽³⁾ Deemed t	Iniversity under Section 3 of the UGC Act, 1956)		
methods - Finite Markov decision		bandit problem (C3, C4).	
process: the agent–environment	3.	Gain an intutive understa	anding of a Markov
interface, goals and rewards, returns,		decision process (C2).	
Markov decision processes, value	4.	Formulate a reinforcement	nt learning task as a
functions, and optimal value functions.		Markov decision process (C5).
Unit 2: Model Free Reinforcement Lea	ırni	ing	
Generalized policy iteration -	1.	Understand policy iteration	on using an iterative
Importance of exploration - Monte		policy evaluation approach	n (C2, C4).
Carlo control - Temporal difference	2.	Understand how policy e	valuation and policy
methods for control.		improvement processes int	teract (C2, C4).
	3.	Solve reinforcement lea	arning tasks using
		Monte Carlo methods (C3,	, C4).
	4.	Combine dynamic progra	amming and Monte
		Carlo ideas to formulate	temporal difference
		methods for solving rein	nforcement learning
		tasks (C5).	
Unit 3: Approximate Solution Methods	s; P	Policy Based Methods	
Value prediction with function	1.	Formulate function approx	ximation methods for
approximation - Gradient-descent		value prediction (C5).	
methods - Linear methods - Control	2.	Understand the assumpti	ons of linear value
with function approximation.		function approximators (C	2).
	3.	Compare and contrast pol	icy-based and value-
Policy gradient - Actor–critic methods		based methods for reir	nforcement learning
- Policy-based vs. value-based		(C6).	
methods - Integrating supervised &	4.	Explore integration of	f supervised and
reinforcement learning.		reinforcement learning (C	5).
Learning strategies, contact hours and	stu	ident learning time	
Learning strategy	Τ	Contact hours	Student learning
			time (Hrs)
Lecture	1	30	60



Quiz			02			04			
Small Group Discussi	ion (SGD)		02			02			
Self-directed learning	(SDL)		-			04			
Problem Based Learn	ing (PBL)		02			04			
Case Based Learning	(CBL)		-			-			
Revision			02			-			
Assessment			06			-			
TOTAL		44			74				
Assessment Methods	5:								
Formative:					Summativ	ve:			
Internal practical Test	t				Sessional	exan	nination		
Theory Assignments					End semes	ster e	examination		
Lab Assignment & V	iva				Viva				
Mapping of assessme	ent with Co	S							
Nature of assessment		CO 1	CO 2	CO 3	CO 4		CO 5		
Sessional Examinatio	n 1	*	*						
Sessional Examinatio	n 2		*	*	*				
Assignment/Presentat	ion	*	*	*	*	*			
End Semester Examin	nation	*	*	*	*		*		
Feedback Process	• Mie	d-Semes	ster feedb	back					
	• Enc	l-Semes	ster Feed	back					
Reference Material	eference 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/SuttonBartoIPRLBoo k2ndEd.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 o	of the P	rogram	:		ME	in Machin	ne Learr	ning						
Course Title: Rei						Reinforcement Learning Lab								
Course	Code:	MCL 60)8L			Course Instructor:								
Academ	nic Yea	ar: 2020-	-2021		Sen	Semester: First Year, Semester 2								
No of C	redits:	: 1			Pre	requisites	: MCL	608						
Synops	sis:	This c	ourse p	orovides	s a pr	actical fo	oundatio	on for im	plement	ing reinfo	orcement			
		learnin	g algoi	rithms f	or rea	l-life pro	blems u	ising state	e of the a	art softwa	re.			
Course	9													
Outcon	nes	On suc	cessful	compl	etion	of this co	urse, st	udents wi	ill be abl	e to				
(COs):														
CO 1:			Understand the tradeoff between exploration vs. exploitation approaches in solving reinforcement learning tasks.											
CO 2:		Use dy	Use dynamic programming approach to solve reinforcement learning tasks.											
CO 3:		Model	Model real-life problems using Markov decision processes.											
CO 4:		Compare and contrast several methods for solving reinforcement learning tasks.												
CO 5: Computationally analyze algorithms for reinforcement learning.														
Mappi	ng of (COs to 2	Pos											
COs	PO 1	<i>PO</i> 2	РО 3	<i>PO</i> 4	PO 5	5 PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11			
CO 1	*	*	*		*									
CO 2	*	*	*		*									
CO 3	*	*	*	*	*									
CO 4	*	*	*	*	*									
CO 5				*	*									
Course	e conte	ent and	outcon	nes:		I				1	·			
Conten	nt -					Compete	encies							
Unit 1	Intro	duction	to the	Reinfo	orcem	ent Lear	ning P	roblem;	Reinfor	cement I	earning			
Frame	work;	Dynam	ic Pro	gramm	ing									
Examples and elements of 1. Implement building blocks for solving a														
reinfor	inforcement learning - Limitations reinforcement learning task (C3).													
and scope of reinforcement learning - 2. Solve an n-Armed bandit problem using different														
History	of rei	nforcem	ent lea	rning.		explo	exploration strategies (C3).							



	3. Implement Markov decision process models
	-
n-Armed bandit problem: action-value	(C3).
methods - Finite Markov decision	
process: the agent–environment	
interface, goals and rewards, returns,	
Markov decision processes, value	
functions, and optimal value functions.	
Unit 2: Model Free Reinforcement Lea	rning
Generalized policy iteration -	1. Implement iterative policy evaluation (C3).
Importance of exploration - Monte	2. Implement Monte Carlo methods for solving
Carlo control - Temporal difference	reinforcement learning tasks (C3).
methods for control.	3. Implement temporal difference methods for
	solving reinforcement learning tasks (C3).
Unit 3: Approximate Solution Methods	s; Policy Based Methods
Value prediction with function	1. Implement function approximation methods
approximation - Gradient-descent	for value prediction (C3).
methods - Linear methods - Control	2. Implement linear value function approximators
with function approximation.	(C3).
	3. Explore integration of supervised and
Policy gradient - Actor-critic methods	reinforcement learning (C5).
- Policy-based vs. value-based	
methods - Integrating supervised &	
reinforcement learning.	
Learning strategies, contact hours and	student learning time
Learning strategy	Contact hours Student learning
	time (Hrs)
Lecture	12 -
Seminar	
Quiz	
Small Group Discussion (SGD)	

-

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Self-directed learning (SDL)



Problem Based Learn	ing (PBL)			-			
Case Based Learning	(CBL)		03			-	
Clinic			-			-	
Practical			24			-	
Revision			03			-	
Assessment			06			-	
TOTAL			48			-	
Assessment Methods	5:						
Formative:					Summati	ive:	
Internal practical Test	-				Sessional	exan	nination
Theory Assignments					End seme	ester e	examination
Lab Assignment & V	iva				Viva		
Mapping of assessme	ent with Co	S					
Nature of assessment		CO 1	CO 2	CO 3	CO 4		CO 5
Sessional Examinatio	n 1	*	*				
Sessional Examinatio	n 2			*	*		*
Assignment/Presentat	ion	*	*	*	*		*
Laboratory examinati	on	*	*	*	*		*
Feedback Process	• Mie	d-Semes	ster feed	back			
	• End	d-Semes	ster Feed	back			
Reference Material	1. Reinford	cement	Learning	: An Inti	oduction, Ri	ichard	S. Sutton and
	Andrew	G. Ba	rto, MIT	Press, 2	and Edition	– Av	ailable online at
	https://w	web.stant	ford.edu/d	class/psych	1209/Reading	s/Sutte	onBartoIPRLBoo
	k2ndEd	.pdf					
	2. Lecture	slides	of Prof.	Emma H	Brunskill – S	Stanfo	ord University –
	Availab	le online	e at http://	web.stanfo	ord.edu/class/	cs234	/schedule.html
	3. Generat	ive Dee	ep Learn	ing: Tead	ching Machi	nes t	o Paint, Write,
	Compos	se, and P	'lay, Davi	d Foster –	O'Reilly, 1st	Editio	on, 2019.
	4. Reinford	cement	Learning and Optimal Control, Dimitri Bertsekas,				
	Athena	Scientifi	c; 1st Ed	tion, 2019			



Name o	of the P	rogram	:		ME	E in Machine Learning								
Course	Title:				Ap	plied Mathematics for Machine Learning								
Course	Code:	MCL 61	6			ourse Instructor:								
Academic Year: 2020-2021Semester: First Year, Semester 2									r 2					
No of C	Credits:	3			Pre	requisites	: MCL	601, 603,	605					
Synops	sis:	This c	ourse j	provide	es a c	comprehe	nsive t	heoretica	al found	ation in a	advanced			
		mather	natical	concep	ots ess	sential for	r develo	oping an	d analyz	ing state	of the art			
		machir	ne learn	ing alg	orith	ns.								
Course	e													
Outcon	nes	On suc	cessful	compl	etion	of this co	urse, st	udents w	vill be ab	le to				
(COs):														
CO	1:		Develop a solid understanding of fundamentals of matrix decomposition techniques and apply them to practical problems.											
CO	2:		÷	-	-		hniques	and asse	ss their ap	plicability	<i>.</i>			
СО	3.	Describ	e the	role of	deriv	vatives in	machir	e learnii	ng and u	inderstand	different			
	5.	methods for computing them.												
CO	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.									of the art					
Mappi	ng of (COs to 1	Pos											
COs	<i>PO 1</i>	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO 5	5 PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11			
CO 1	*	*	*											
CO 2	*	*												
CO 3	*		*											
CO 4		*	*	*		*								
CO 5		*	*	*	*				*					
Course	e conte	ent and	outcon	nes:	I		·	I						
Conten	at					Compet	encies							
Unit 1	Matri	ix Deco	mposit	ions ar	nd Ap	oplicatior	IS							
Matrix	and	tens	or p	roducts	_	1. Dev	elop i	deas fo	r matrix	k decom	positions			
Determ	inant	anc	-] 1	race	_	usin	g block	matrix 1	represent	ations (C	5).			
Eigend					and	2. Con	ipare a	nd contr	ast exact	t and app	roximate			
diagona	alizatio	on	-	Chole	esky	decompositions in terms of construction and								
decom	positio	n -	Singu	lar v	alue	applications.								
-		n - No	-			3. Und	erstand	the op	timizatio	n-centric	view to			



^{VSp} IRED BY ^{VS} (Deemed to	b be University under Section 3 of the UGC Act, 1956)				
factorization.	matrix factorization (C3).				
	4. Interpret the factors arising	out of matrix			
	factorizations for real-life proble	ems (C3).			
Unit 2: Computing Derivatives					
Differentiability - Symbolic	1. Understand multivariable of	lifferentiability			
differentiation - Finite differences -	theory (C3).				
Automatic differentiation.	2. Understand the basics	of symbolic			
	differentiation (C3).				
	3. Develop ideas for approximati	ng derivatives			
	using finite differences (C5).				
	4. Understand the basics of	of automatic			
	differentiation and compare	it with other			
	approaches (C3, C6).				
Unit 3: Continuous Optimization					
Optimization using gradient descent -	1. Understand the basics of	f continuous			
Constrained optimization and Lagrange	optimization (C3).				
multipliers - Convex optimization -	 Visualize constrained optimization problems and solutions in 3D (C3). Understand convexity and its importance in machine learning (C3). 				
Subgradients - Stochastic gradient					
descent - Momentum methods.					
	4. Understand gradient descent n	nethod and its			
	extensions for continuous optim	ization (C4).			
Learning strategies, contact hours and					
Learning strategy	Contact hours Stud	0			
	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	5:						
Formative:					Summati	ive:	
Internal practical Test			Sessional	examination			
Theory Assignments					End seme	ester examination	
Lab Assignment & V	iva				Viva		
Mapping of assessm	ent with Co	s					
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CO 5	
Sessional Examinatio	n 1	*	*				
Sessional Examinatio	n 2		*	*	*		
Assignment/Presentat	ion	*	*	*	*	*	
End Semester Examin	nation	*	*	*	*	*	
Feedback Process	• Mi	1-Seme	ster feed	back		I	
			ster Feed				
Reference Material	10. Mathem	atics for	Machine	e Learning	by Marc Pet	ter Deisenroth, A Aldo	
			-	÷		surce from Cambridge	
		•	ss availa	ble at ht	tps://mml-boo	ok.github.io/book/mml	
	book.pd				~		
		•				Charles F. Van Loan	
					on edition, 201		
	MIT	-	ss,2017.	nenow, r	Available	o, and Aaron Courville e online a	
				_ book.org/	Available		
	-	-		-	From Theory	to Algorithms (UML)	
		-		-	-	oridge University Press	
	1st Edit					J	



Name o	of the P	rogram	:		ME	in l	Machin	1E in Machine Learning							
Course	Title:				Ap	Applied Mathematics for Machine Learning Lab									
Course	Code:	MCL 61	6L		~ ~		e Instru								
Academ	nic Yea	nr: 2020-	2021		Sen	nes	ter: Firs	st Year, S	Semester	2					
No of C	Credits:					-	-	MCL 6							
Synop	sis:	This co	ourse pi	rovides	a co	mp	rehensi	ve com	putation	al found	ation in a	advanced			
		mather	natical	concept	ts es	sen	tial for	develop	ping and	l analyzi	ng state o	of the art			
		machir	ne learn	ing algo	orithi	ms.									
Course	e														
Outco	mes	On suc	cessful	comple	etion	of	this cou	urse, stu	dents wi	ill be abl	e to				
(COs):															
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:	O 5: Understand the implementations of state of the art optimization algorithms used in machine learning libraries.									is used in					
Mappi	ng of (COs to 1	Pos												
COs	<i>PO 1</i>	<i>PO 2</i>	<i>PO 3</i>	<i>PO</i> 4	PO	5	PO 6	<i>PO</i> 7	<i>PO</i> 8	<i>PO</i> 9	PO 10	PO 11			
CO 1	*	*	*		*										
CO 2	*	*	*		*										
CO 3	*	*	*	*	*										
CO 4	*	*	*	*	*		*								
CO 5				*	*										
Course	e conte	ent and	outcom	nes:	1		<u> </u>			-1	1	<u>. </u>			
Conten	nt					C	ompete	ncies							
Unit 1	: Matr	ix Deco	mposit	ions an	d Ar	opli	ication	s							
Matrix	and	tens	or pr	oducts	-	1.	Imple	ement n	natrix de	ecompos	itions usi	ng block			
Determ	ninant	and	l t	race	-		matri	x repres	sentation	as (C3).					
Eigend	ecomp	osition		;	and	2.	-	ement	and	compar		ct and			
diagon	alizatio														
decom	positio	n -	Singul	ar va	alue	3.	Imple	ement	codes	to	understa	nd the			
decom	positio	n - No	onnegati	ive ma	trix		optin	nization	-centric	view	to to	matrix			



^W SPIRED BY LIFT (Deemed	to be L	Iniversity under Section 3 of the UGC Act, 1956)						
factorization.		factorization (C3).						
	4.	Interpret the factors ari	sing out of matrix					
		factorizations for real-life problems (C3).						
Unit 2: Computing Derivatives								
Differentiability - Symbolic	1.	Visualize differentiability	concepts in 3D (C4).					
differentiation - Finite differences -	2.	Implement symbolic	differentiation for					
Automatic differentiation.		computing derivatives exa	ctly (C3).					
	3.	Implement finite differ	rence methods for					
		approximating derivatives	(C3).					
	4.	Implement automatic	differentiation and					
		compare it with other appr	roaches (C3, C6).					
Unit 3: Continuous Optimization	1							
Optimization using gradient descent - Constrained optimization and Lagrange multipliers - Convex optimization – Subgradients - Stochastic gradient descent - Momentum methods.	2.	 Solve continuous optimization problems state of the art libraries (C3). Visualize constrained optimization pro and solutions in 3D (C3). Implement and visualize solutions of g descent method and its extension continuous optimization (C4). Understand implementations of cont optimization algorithms used in state of 						
Learning strategies, contact hours and	l stu	ident 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	8:							
Formative:					Summati	ve:		
Internal practical Test					Sessional	exan	nination	
Theory Assignments					End seme	ster e	examination	
Lab Assignment & Vi	iva				Viva			
Mapping of assessme	ent with Co	s			- 1			
Nature of assessment		CO 1	CO 2	CO 3	CO 4		CO 5	
Sessional Examination	n 1	*	*					
Sessional Examination	n 2			*	*	* *		
Assignment/Presentat	ion	*	*	*	*	*		
Laboratory examination	on	*	*	*	*	* *		
Feedback Process	• Mic	l-Semes	ster feed	back	·			
	• Enc	l-Semes	ter Feed	back				
Reference Material	 End-Semester Feedback 1. 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 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						ME in Machine Learning								
Course	Course Title:					Natural Language Processing Principles & Applications								
						Course Instructor:								
Acader	Academic Year: 2020-2021 Se						st Year	, Semester	r 2					
No of C	Credits	: 3			Prer	equisites	: MCL	601, 603						
Synop	sis:	This co	ourse p	rovides	a thore	ough intr	oductio	n to funda	amental co	oncepts ar	nd modern			
		algorith	nms in n	atural la	anguage	process	ing.							
Course	e													
Outco	mes	On suc	cessful	compl	etion o	f this co	ourse, st	udents w	ill be abl	e to				
(COs):	Os):													
CO	1:	Gain a	thoroug	h intro	duction	to funda	mental	concepts a	and ideas	in natural	language			
		process	Ų											
CO	2:		•	-		•		e	-	÷	linguistic			
										al languag				
CO	3:	-				, and sen	nantic p	rocessing	from both	n a linguis	tic and an			
	4.	-	mic per	-				11-						
CO	4:	Formulate deep learning approaches for natural language processing tasks.												
CO	CO 5: Develop practical experience with state of the art natural language processing tool and libraries.								sing tools					
Mappi	Mapping of COs to POs													
COs	PO 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11			
CO 1	*													
CO 2	*			*										
CO 3	*	*	*	*										
CO 4		*	*	*	*									
CO 5		*	*	*	*				*					
Course	e conte	ent and	outcon	nes:							1			
Conten	ıt				(Compet	encies							
Unit 1	: Intro	oductior	n to Na	tural]	Langua	age Pro	cessing	(NLP);	Regular	Express	sions; N-			
gram l	Langu	age Mo	dels											
Termir		- Prohal	nility ar	nd NI F		1 Und	erstand	the has	sics of I	NLP and	role of			
Terminology - Probability and NLP 1. Understand the basics of NLP and role of											1010 01			
						probability in it (C3).- 2. Understand how to use and apply regular								
Introdu	iction	to regul	lar exn	ression	IS - 1	2 Und	erstand	how to) lise a	nd annly	regular			
		to regul	-						o use a	nd apply	regular			
	ation	to regul extractio	-		gular	expr	essions	(C3).			regular language			



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



Assessment			06			-	
TOTAL	TOTAL					74	
Assessment Methods	5:						
Formative:					Summati	ive:	
Internal practical Test	t				Sessional	exam	ination
Theory Assignments					End seme	ester ex	xamination
Lab Assignment & V	iva				Viva		
Mapping of assessm	ent with Co	s					
Nature of assessment		CO 1	CO 2	CO 3	CO 4		CO 5
Sessional Examinatio	on 1	*	*				
Sessional Examinatio	on 2		*	*	*		
Assignment/Presentat	tion	*	*	*	*		*
End Semester Examin	nation	*	*	*	*		*
Feedback Process	 Mid-Semester feedback End-Semester Feedback 						
Reference Material	Pearson https://v 2. Natural Natural Loper, https://v 3. A Prime Yoav http://fa 4. Natural	rd Edit ford.edu/~ ge Proces age Tool Ltd., 1 k.org/boo ural Netv ldberg e.tamu.ed age Proce	ion (dra ~jurafsky/s ssing with kit, Steven st Edition k/ vork Mode – u/huangrh/	ft) – A slp3/ Python. – A n Bird, Ewa n, 2017 - els for Natura Available /Spring18/nnl th PyTorch,	Availat nalyzin n Klei Availa l Langu p.pdf	ng Text with the in, and Edward	



Name of the Program:						ME in Machine Learning								
					Natural Language Processing Principles and Applications									
						Lab								
		MCL 61				irse Instru		<u> </u>	2					
Acader No of (ar: 2020-	2021			nester: Firs			2					
				rovidos		requisites: prough con			dation to	the oppli	actions of			
Synop	515:					ige processi		inal louin		the appli	cations of			
Cours	ρ	argonni			ingua	ige processi	ing.							
Outco	-	On suc	cessful	comple	etion	of this cou	ırse, stu	dents wi	ill be abl	e to				
(COs):	:													
CO 1:		Gain a process		h introd	uctior	n to fundan	nental co	oncepts a	nd ideas	in natural	language			
CO 2:						standing ong computa		U	-	U	U			
CO 3:		Analyze word-level, syntactic, and semantic processing from both a linguistic and an algorithmic perspective.								tic and an				
CO 4:		Formulate deep learning approaches for natural language processing tasks.												
CO 5:	Develop practical experience with state of the art natural language processing to and libraries.								sing tools					
Mappi	ing of (COs to 1	Pos											
COs	<i>PO</i> 1	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PO	5 PO 6	<i>PO</i> 7	<i>PO</i> 8	<i>PO</i> 9	PO 10	PO 11			
CO 1	*	*	*		*									
CO 2	*	*	*		*									
CO 3	*	*	*	*	*									
CO 4	*	*	*	*	*									
CO 5				*	*									
Course	e conte	ent and	outcom	nes:	•				•					
Conter	ıt					Competencies								
Unit 1	: Intro	duction	n to Na	tural L	angu	age Proc	essing	(NLP);	Regular	Express	sions; N-			
gram l	Langua	age Mo	dels											
Termir	nology	- Probał	oility an	d NLP		1. Unde	rstand	the basi	ics of 1	NLP and	role of			
						probability in it (C3).								
				Introduction to regular expressions -										
Introdu	iction	to regul	ar exp	ressions	5 -	-	•			nd apply	regular			



"SPIRED BY SS (Deemed to	o be University under Section 3 of the UGC Act, 1956)				
expressions.	3. Develop the idea of a probabilistic language				
	model (C5).				
Probabilistic language model - Chain	4. Understand how to evaluate and compare				
rule and Markov assumption -	language models (C6).				
Evaluating language models –					
Smoothing.					
Unit 2: Naive Bayes and Sentiment Cla	ssification; Vector Semantics and Embeddings				
Vector semantics - Words and vectors -	1. Implement sentiment classification using real-				
Cosine for measuring similarity - TF-	life datasets (C3).				
IDF vector model - Word2Vec &	2. Implement building blocks for vector				
GloVe models - Visualizing	representation of words (C5).				
embeddings.	3. Implement and compare vector models for				
	words (C6).				
	4. Visualize word embeddings (C3).				
Unit 3: NLP with Deep Learning; App	lications of Natural Language Processing				
Neural language models - Introduction	1. Implement neural models for NLP applications				
to PyTorch -Sequence processing with	(C3).				
recurrent neural networks	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	24				
Revision			03			-		
Assessment			06			-		
TOTAL			48			-		
Assessment Methods	5:		•					
Formative:					Summati	ve:		
Internal practical Test					Sessional	exam	nination	
Theory Assignments					End seme	ester e	xamination	
Lab Assignment & V	iva				Viva			
Mapping of assessme	ent with Co	S						
Nature of assessment		CO 1	CO 2	CO 3	CO 4		CO 5	
Sessional Examinatio	n 1	*	*					
Sessional Examinatio	n 2			*	*		*	
Assignment/Presentat	ion	*	*	*	*	*		
Laboratory examinati	on	*	*	*	*		*	
Feedback Process	• Mi	d-Semes	ster feed	back	•			
	• En	d-Semes	ster Feed	back				
Reference Material								



Name of the Program: M						ME in Machine Learning							
Course	Title:				Con	Convolutional Neural Networks for Computer Vision							
Course	Code:	MCL 61	8		Cou	Course Instructor:							
Academ	nic Yea	nr: 2020-	2021		Sem	ester: Fin	st Year,	Semester	2				
No of C	Credits:	3			Prer	requisites	: MCL	601, 603					
Synop	sis:	This co	ourse p	rovides	s a the	oretical fo	oundatio	on for the	applicati	on of con	volutional		
		neural r	network	s to con	nputer	vision.							
Course	e												
Outco	mes	On suc	cessful	compl	etion o	of this co	urse, st	udents wi	ll be ab	le to			
(COs):													
CO	1:	Underst	tand the	differe	nce bet	ween ima	ige proc	essing and	compute	er vision.			
CO		applicat	tion of (CNNs ir	n comp	uter visio	n.	to gain h					
CO	3:	Analyz	e a real-	life pro	blem ir	nvolving o	compute	er vision ar	nd solve	it using Cl	NNs.		
CO	4:	Decide	how to	choose	an exis	ting CNN	V archite	ecture for a	n applica	ation prob	lem.		
CO	5:	Develo	p practio	cal expe	rience	with state	e of the	art deep le	arning to	ols and lit	oraries.		
Mappi	ng of (COs to 1	POs										
COs	PO 1	PO 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11		
CO 1	*												
CO 2	*	*	*										
CO 3		*	*		*								
CO 4		*	*	*	*								
CO 5		*	*	*	* * * *								
Course	e conte	ent and	outcon	nes:					·				
Conten	nt					Compete	encies						
Unit 1	: Intro	duction	to Co	nputer	· Visio	on; Featu	ires; N	eural Net	works]	Basics			
Compu	Computer vision overview - Historical 1. Compare and contrast computer vision an									sion and			
context	t and	applic	ations	- In	nage	ge image processing (C6).							
process	sing vs.	. compu	ter visi	on		2. Understand how to build features in the							
Histog	ram of	oriented	l gradie	ents (H	OG)	cont	ext of c	omputer	vision ((C4).			
- Sc	ale-inv	ariant	feature	transf	form	3. Com	ipare a	and cont	rast di	fferent (ypes of		
(SIFT)	- Spe	eeded-uj	p robu	st feat	ures	featu	res for	computer	vision	(C6).			
(SURF	^r) -	Limita	tions	of h	and-	4. Exte	nd id	eas from	n neur	al netw	orks to		



Deemed to Deemed to	to be University under Section 3 of the UGC Act, 1956)
engineered features.	computer vision (C2).
Multi-layer perceptron: architecture	
and parameter learning.	
Unit 2: Convolutional Neural Network	s (CNN)
Network layers: pre-processing,	1. Understand the building blocks of a CNN
convolutional layers, pooling layers,	(C4).
nonlinearity, fully connected layers,	2. Understand the purpose and interconnectivity
region of interest pooling - Loss	of different types of CNN layers (C4).
functions: hinge loss, squared hinge	3. Understand the role of nonlinear activation
loss, cross-entropy loss, Euclidean loss,	functions in a CNN (C4).
L1 error.	4. Understand different types of loss functions
	used in a CNN (C4).
Unit 3: CNN Learning; Visualizing and	d Understanding CNNs
Weight initialization – Regularization - Gradient based learning: batch-, stochastic-, and mini-batch gradient descent, gradient computations in CNN.	 Understand the importance of random initialization of weights in a CNN (C2). Understand the role of regularization in preventing overfitting (C4). Understand different gradient based approaches for optimization (C2). Understand how gradients can be efficiently computed in a CNN (C4).
Unit 4: CNN Architectures; Application	ns of CNNs in Computer Vision
Image classification, Object detection and localization.	 Explore the building blocks of state of the art CNN architectures (C4). 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			
(SDL)		-			04			
ing (PBL)		02	02			04		
(CBL)		-	-					
		02			-			
		06			-			
		44			74			
:								
				Summativ	ve:			
Internal practical Test				Sessional e	exam	ination		
				End semes	ter ex	xamination		
Lab Assignment & Viva				Viva				
ent with Co	s							
Nature of assessmentCO				CO 4		CO 5		
n 1	*	*						
n 2		*	*	*				
ion	*	*	*	*		*		
ation	*	*	*	*	*			
• Mic	1-Semes	ster feedl	pack					
1. A Guid	e to Co	onvolutio	nal Neural	Networks for	or Co	omputer Vision,		
Salman	Khan, H	Iossein R	ahmani, Sy	ed Afaq Ali S	Shah,	and Mohammed		
Bennam	ioun, Mo	organ & C	rgan & Claypool Publishers, 2018.					
2. Lecture	slides c	of Prof. F	Fei-Fei Li	– Stanford U	nivers	sity – Available		
online a	t http://c	s231n.sta	nford.edu/					
3. Neural Networks				g, Michael N	ielser	n, Determination		
Press				able	onli	ine at		
http://neuralnetw				orksanddeeplearning.com/index.html				
4. Computer Visio				1 Application	ns, R	ichard Szeliski,		
Springer	r, 2011	– Onl	ine resou	rce from Sp	pringe	er available at		
http://sz	eliski.or	g/Book/						
	(SDL) ing (PBL) (CBL	(SDL) ing (PBL) (CBL) (CBL) ing (PBL) (CBL) (CBL) ing (PBL) (CBL) (CBL) CO 1 n 1 * CO 1 n 1 * CO 1 n 1 * CO 1 n 1 * Mid-Semester Mid-Semester Mid-Semester I. A Guide to Co Salman Khan, F Bennamoun, Mo 2. Lecture slides of online at http://c 3. Neural Network Press http://neuralnetw 4. Computer Visio Springer, 2011	(SDL)-ing (PBL)02(CBL)-020204020544443:in 2CO 1CO 1CO 2n 1*ation**ion*ion*ation*1ACO 1CO 2n 1*ation*2-ion*ation*1AOld-Semester feedleEnd-Semester Feedle1. A Guide to Convolution Salman Khan, Hossein R Bennamoun, Morgan & O2. Lecture slides of Prof. F online at http://cs231n.sta3. Neural Networks and De PressPress-http://neuralnetworksando4. Computer Vision: Algo	(SDL) - ing (PBL) 02 (CBL) - 02 06 44 44 s: iva Ent with Cos CO 1 CO 2 CO 3 n 1 * * * n 2 . * * ion * * * ation * * * Nid-Semester feedback End-Semester feedback * I. A Guide to Convolutional Neural Salman Khan, Hossein Rahmani, Sy Bennamoun, Morgan & Claypool Pu 2. Lecture slides of Prof. Fei-Fei Lioonline at http://cs231n.stanford.edu/ 3. Neural Networks and Deep Learnin Press — Availa http://neuralnetworksanddeeplearnin 4. Computer Vision: Algorithms and Springer, 2011 – Online resource Online resource Springer, 2011 – Online resource	(SDL) - ing (PBL) 02 (CBL) - 02 06 44 44 Summative Sessional of End semes Viva Viva ent with Cos CO 1 CO 2 CO 3 CO 4 n 1 * * * * n 2 . * * * * ion * * * * * * * e Mid-Semester feedback *	(SDL)-04ing (PBL)0204(CBL)02-06-4474Summative:Sessional examEnd semester exVivaVivaVivaVivaVivaVivaVivaVivaVivaVivaVivaVivaVivaVivaVivaVivaVivaNote: Colspan="2">VivaNote: Colspan="2">VivaNote: Colspan="2">Viva		



Name of	of the P	rogram	:		ME in Machine Learning							
Course	Title:				Cor	Convolutional Neural Networks for Computer Vision Lab						
Course	Code:	MCL 61	8L		Course Instructor:							
Acader	nic Yea	nr: 2020-	2021		Sen	nest	er: First	Year, Se	emester	2		
No of C	Credits:	: 1			Pre	requ	uisites: 1	MCL 61	8			
Synop	sis:	This c	course	provide	s a	cc	omputati	onal fo	undation	n for t	he applic	cation of
		convolu	itional ne	eural net	worl	ks to	comput	er visior	ı.			
Course	e											
Outco	mes	On suc	cessful d	complet	ion	of t	his cour	se, stud	ents wi	ll be abl	e to	
(COs):	:											
CO 1:		Implem	ent imag	e proces	sing	; and	l comput	er visio	n tasks.			
CO 2:		Apply C	Apply CNNs for computer vision problems.									
CO 3:		Analyze	e a real-li	fe probl	em i	nvo	lving co	mputer v	vision an	d solve i	t using CI	NNs.
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.							oraries.			
Mappi	ng of (COs to 1	Pos									
COs	<i>PO 1</i>	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	PC	5 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11
CO 1	*	*	*		*							
CO 2	*	*	*		*							
CO 3	*	*	*	*	*							
CO 4	*	*	*	*	*							
CO 5				*	*					*		
Course	e conte	ent and	outcom	es:								
Conten	nt					Co	mpeten	cies				
Unit 1	: Intro	duction	to Com	puter \	Visi	on;	Featur	es; Neu	ral Net	works l	Basics	
Compu	iter vis	ion ove	rview -	Historie	cal	1.	Impler	nent ba	isic cor	nputer	vision an	d image
contex	t and	applic	ations	- Ima	ige		proces	sing tas	ks (C3)			
process	sing vs	. compu	ter visio	n		2.	Build	feature	s in tl	ne cont	ext of c	computer
Histog	ram of	oriented	l gradier	nts (HO	G)		vision	(C3).				
- Sc	ale-inv	ariant	feature	transfo	rm	3.	Compa	are and	d cont	rast di	fferent t	ypes of
(SIFT)	- Spe	eeded-uj	p robus	t featur	res		feature	es for co	omputer	vision ((C6).	
(SURF	r) -	Limitat	tions o	of har	nd-	4.	Impler	nent a	nd ext	end ide	eas from	n neural
engine	ered fe	atures.					networ	ks to co	omputer	vision	(C3).	



Multi lavan nanontrone anglita sture	
Multi-layer perceptron: architecture	
and parameter learning.	
Unit 2: Convolutional Neural Network	ks (CNN)
Network layers: pre-processing,	1. Visualize and understand the building blocks
convolutional layers, pooling layers,	of a CNN (C4).
nonlinearity, fully connected layers,	2. Implemnt different types of CNN layers and
region of interest pooling - Loss	understand their utility (C4).
functions: hinge loss, squared hinge	3. Implement different nonlinear activation
loss, cross-entropy loss, Euclidean loss,	functions, compare and contrast them (C6).
L1 error.	4. Implement and understand the role of different
	types of loss functions used in a CNN (C4).
Unit 3: CNN Learning; Visualizing an	nd Understanding CNNs
Weight initialization – Regularization – Gradient based learning: batch-, stochastic-, and mini-batch gradient descent, gradient computations in CNN. Unit 4: CNN Architectures; Applicatio	 Implement random initialization of weights in a CNN and compare it with a nonrandom initialization (C6). Implement regularization to prevent overfitting in CNNs (C3). Implement different gradient based approaches for optimization (C3). Implement efficient gradient computations in CNNs (C4).
Unit 4: UNN Architectures; Applicatio	ons of CIVINS in Computer Vision
Image classification, Object detection	1. Explore the building blocks of state of the art
and localization.	CNN architectures (C4).
	2. Explore applications of CNNs to real life
	problems (C3).
Learning strategies, contact hours and	d student learning time
Learning strategy	Contact hours Student learning time (Hrs)
Lecture	12 -
Seminar	



Quiz			-			-		
Small Group Discuss	ion (SGD)		-			-		
Self-directed learning	g (SDL)		-			-		
Problem Based Learn	ning (PBL)		-		-			
Case Based Learning	(CBL)		03			-		
Clinic			-			-		
Practical			24			-		
Revision	03			-				
Assessment	06			-				
TOTAL	48			-				
Assessment Method	s:							
Formative:					Summati	ve:		
Internal practical Tes			Sessional	examination				
Theory Assignments					End semester examination			
Lab Assignment & V			Viva					
Mapping of assessm	ent with Co	S						
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CO 5		
Sessional Examination	on 1	*	*					
Sessional Examination	on 2			*	*	*		
Assignment/Presenta	tion	*	*	*	*	*		
Laboratory examination	ion	*	*	*	*	*		
Feedback Process			ster feedl ster Feed					
Reference Material	Salman Bennam 2. Lecture online a 3. Neural I Press – 4. Compute	Khan, H noun, Mo slides o t http://c Network http://ne er Visio	Hossein R organ & C of Prof. H es231n.sta s and De uralnetwo on: Algo	ahmani, Sy Claypool Pu Fei-Fei Li anford.edu/ eep Learnin orksanddee orithms and	ved Afaq Ali Iblishers, 201 – Stanford U ng, Michael I <u>plearning.cor</u>	Jniversity – Availa Nielsen, Determina n/index.html ons, Richard Szeli	med able tion	



Name	of the F	Program	•		ME in	n Machi	ne Learni	ng					
Course		0				preneurs		0					
Course	Code:	ENP 60	1		Cour	Course Instructor:							
Acader	nic Yea	ar: 2020	-2021		Seme	Semester: First Year, Semester 2							
No of (Credits	: 3			Prere	equisites	:						
Synop	sis:	This c	course	introdu	ices sti	udents	to the	theory of	entrepre	neurship	and its		
		practic	al imp	olemen	tation.	It foc	uses or	n differer	nt stages	related	to the		
		entrepr	reneuria	al proc	ess, in	cluding	busine	ss model	innovatio	on, mone	tization,		
		small	busines	s mana	igemen	t as we	ll as stra	ategies that	at improv	e perform	ance of		
		new bu	isiness	ventur	es. Cen	tered or	n a mixt	ure of the	pretical ex	xploration	as well		
		as case	e studie	s of rea	al-world	d examj	ples and	guest lect	ures, stud	lents will	develop		
		an und	erstand	ling of	success	ses, opp	ortunitie	s and risk	s of entre	preneursh	ip. This		
		course	has an	interdi	isciplin	ary app	roach ar	d is there	fore open	to studer	nts from		
		other N	Aajors.										
Cours	e												
Outco	mes	On suc	cessful	compl	etion of	f this co	ourse, stu	idents will	l be able t	0:			
(COs)	:												
CO 1			stand the entures.		s of en	trepren	eurial sk	ills and co	ompetenci	ies for cre	ation of		
CO 2					conceprial tale	-	overview	of entrep	oreneursh	ip with a	view to		
CO 3				±			s startin	g with pre	-venture	stage.			
CO 4		Create	and ex	ploit in	novativ	ve busin	ess idea	s and marl	ket opport	tunities.			
CO 5				d-set fo tunities		g on de	eveloping	g novel a	ınd uniqu	ie approa	ches to		
Mappi	ing of	COs to	11										
COs	<i>PO 1</i>	PO 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11		
CO 1	*												
CO 2				*									
CO 3			*										
CO 4						*							
CO 5								*					
Cours	e conte	ent and	outcon	nes:		ı			I		<u> </u>		
Conter	ıt				(Compet	encies						
Unit 1	: Intro	duction	to En	treprer	neurshi	i p							



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



2.	Eva	aluate o	oneself a	nd plan c	ourses of action
	to	help	develop	one's	entrepreneurial
	cha	racteris	stics and o	competen	cies (C5).

					characteristics and competencies (C5).						
Learning strategies,	contact hou	irs and s	student learn	ing time							
Learning strategy			Contact hou	urs	S	Student learning					
					ti	time (Hrs)					
Lecture			30		6	0					
Quiz	02		0	4							
Small Group Discuss	ion (SGD)		02		0	2					
Self-directed learning	g (SDL)		-		0	4					
Problem Based Learn	ning (PBL)		02		0	4					
Case Based Learning	-		-								
Revision			02		-						
Assessment	06		-								
TOTAL	44		7	74							
Assessment Method	s:										
Formative:				Summa	Summative:						
Internal practical Tes	t			Session	Sessional examination						
Theory Assignments				End sen	End semester examination						
Lab Assignment & V	'iva			Viva	Viva						
Mapping of assessm	ent with Co	S									
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CO 5	CO 6				
Sessional Examination	on 1	*	*								
Sessional Examination 2				*	*						
Assignment/Presenta	tion					*	*				
End Semester Exami	*	*	*	*	*						
Feedback Process	• Mi	d-Semes	ter feedback	1	L						
	• End	d-Semest	er Feedback								
Reference	1. NVR	Naidu	and T.	Krishna	Rao, "N	lanageme	ent and				



Material	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.



Name of t	he P	rogram	:		ME in l	Machine	Learnin	ıg			
Course Ti	itle:				Entrepreneurship Lab						
Course Co	ode:	ENP 60	1L		Course Instructor:						
Academic	e Yea	r: 2020-	2021		Semest	er: First	Year, S	emester	2		
No of Cre	dits:	1			Prerequisites: MCL 618						
Synopsis	:	This c	ourse ir	ntroduce	es stude	ents to	the the	eory of	entrepr	eneurship	o 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. Centered 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.									etization, mance of ration as lents will risks of
Course							<u>j</u>	-			
Outcomes On successful completion of this course, students will be able to											
(COs):											
CO 1		of new	venture	s.							creation
CO 2			arize wit e entrep				rview o	of entrep	reneurs	hip with a	a view to
CO 3				_	_					re stage.	
CO 4										ortunities	
CO 5		market	opportu		using o	n devel	oping	novel a	na uniq	ue appro	oaches to
Mapping	g of (COs to 1									
COs P	01	<i>PO</i> 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11
CO 1 *											
CO 2				*							
CO 3			*								
CO 4						*					
CO 5								*			
Course c	onte	nt and	outcom	es:			1				<u> </u>
Content					Ca	mpeten	cies				
Unit 1: Iı	ntro	duction	to Entr	eprene	urship						
Meaning		and	Definit	ion	of	1. Ex	plain t	the mea	aning c	of Entrep	preneurship
Entrepren	neurs	hip-Em	ploymer	nt	VS	(C	1).				



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



			characteri	stics and co	ompetencies (C5).	
Learning strategies, contact ho	urs and	student	learning	time		
Learning strategy		Conto	act 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:				Summa	tive:	
Internal practical Test				Sessional examination		
Theory Assignments				End sem	ester examination	
Lab Assignment & Viva				Viva		
Mapping of assessment with Co	DS					
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5	
Sessional Examination 1	*	*				
Sessional Examination 2			*	*	*	
Assignment/Presentation	*	*	*	*		
1 issignment i resentation	Laboratory examination *				*	



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.										



Name	of the P	rogram	:		ME	in Machi	ne Learni	ng							
Course		0			Min	ni Project ·	- 2	0							
Course	Code:	MCL 69	6		Cou	Course Instructor:									
Acader	nic Yea	ar: 2020	-2021		Sen	Semester: First Year, Semester 2									
No of (Credits	: 4			Pre	Prerequisites: Programming in Python / R									
Synop	sis:	Studen	ts are e	expecte	d to s	elect a p	roblem ii	n the area	a of the	ir interest	t and the				
		area of	their s	peciali	zation	that wo	uld requi	re an imj	plement	ation in h	nardware				
		/ softw	are or b	ooth in	a sem	nester									
Cours	e														
Outco	mes	On suc	cessful	compl	etion	of this co	ourse, stu	dents wil	ll be abl	e to					
(COs)	:														
CO	1	Apply the objectives of the project work and provide an adequate background													
CO		with a detailed literature survey													
CO		Breakc	Breakdown the project into sub blocks with sufficient details to allow the												
CU		work to be reproduced by an independent researcher													
CO	3	Compose hardware/software design, algorithms, flowchart, methodology, and													
CO	5	block diagram													
CO	4	Evalua	te the r	esults											
CO	5	Summ	arize th	e work	carrie	ed out									
Mappi	ing of (COs to]	POs												
<u> </u>	PO 1	DO 3	DO 3	DO 4	DO 5		DO 7	DO 9	DO 0	DO 10	DO 11				
COs	POT	<i>PO 2</i>	<i>PO 3</i>	<i>PO 4</i>	<i>PO</i> 5	F PO 6	<i>PO</i> 7	PO 8	PO 9	PO 10	PO 11				
CO 1 CO 2				•	*			*							
CO 2 CO 3							*			*					
						*					*				
CO 4						~	*				~				
CO 5							*								
		ent and	outcon	nes:		9	•								
Conter						Compet	encies								
Phase		dantifi -	ation		main	A + +1=	nd of the	toniast	dont al-	and he -	hla ta				
Proble		dentific		sync	-			-		ould be a					
submis	,	status	submis	ssion,	mid		•			ation (C1)				
evalua	tion.					2. Disc	cuss the p	project (C	2)						



ASPIRED BY LIFE (Deem	ed to be University under Section 3 of the UGC Act, 1956)									
	3. Prepare the outline (C3)									
	4. Describe the status of the	e project (C2)								
	5. Prepare a mid-term proje	ect presentation report								
	(C3)									
	6. Prepare and present	Prepare and present mid-term project								
	presentation slides (C3, C	presentation slides (C3, C5)								
	7. Develop project	implementation in								
	hardware/software or bo	th in chosen platform								
	(C5)									
Phase 2										
Status submission, final evaluation.	1. Prepare the progress repo	ort (C3)								
	2. Prepare the final project	ct presentation report								
	(C3)									
	3. Prepare and present fina	al project presentation								
	slides (C3, C5)									
	4. Modify and Develop	implementation in								
	hardware/software or bo	th in chosen platform								
	(C3, C5)									
	5. Justify the methods used and obtained results									
	(C6)									
Learning strategies, contact hours an	d 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:				ve:				
Project Problem Selection	on			Mid-Term Presentation				
Synopsys review	Second status review							
First status review				Demo & I	Final Presentation			
Mapping of assessmen	t with Cos							
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5			
Mid Presentation	*	*						
Presentation	*	*	*	*	*			
Feedback Process	End-Semes	ter Feedl	back					
Reference Material P	Particular to the ch	osen pro	ject					



CO 1Image: Construct of the second secon	content.											
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 write a technical report. 5. Develop ability to work in groups to review and modify technical Course On successful completion of this course, students will be able to (COs): Show competence in identifying relevant information, definiexplaining topics under discussion. CO 1 Show competence in working with a methodology, structuring the work, and synthesizing information. Use appropriate registers and vocabulary, and will demonstrate com	content.											
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 write a technical report. 5. Develop ability to work in groups to review and modify technical Course On successful completion of this course, students will be able to (COs): Show competence in identifying relevant information, define explaining topics under discussion. Show competence in working with a methodology, structuring the work, and synthesizing information. Use appropriate registers and yocabulary, and will demonstrate communication Use appropriate registers and yocabulary.	content.											
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 write a technical report. 5. Develop ability to work in groups to review and modify technical Course Outcomes On successful completion of this course, students will be able to (COs): Co1 Show competence in identifying relevant information, define explaining topics under discussion. CO2 Work, and synthesizing information.	content.											
CourseOn successful completion of this course, students will be able to (COs):CourseOn successful completion of this course, students will be able to (COs):CourseShow competence in identifying relevant information, definiexplaining topics under discussion.CourseShow competence in working with a methodology, structuring the work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate complete comple	content.											
3. To prepare a topic and deliver a presentation.4. To develop the skill to write a technical report.5. Develop ability to work in groups to review and modify technicalCourse Outcomes (COs):On successful completion of this course, students will be able to(COs):CO 1Show competence in identifying relevant information, define explaining topics under discussion.CO 2Show competence in working with a methodology, structuring the work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate completed to the structure of the	content.											
4. To develop the skill to write a technical report.5. Develop ability to work in groups to review and modify technicalCourse Outcomes (COs):On successful completion of this course, students will be able toCO1Show competence in identifying relevant information, defini explaining topics under discussion.CO2Show competence in working with a methodology, structuring the work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate complete complet	content.											
Course Outcomes (COs):On successful completion of this course, students will be able to On successful completion of this course, students will be able to (COs):CO 1Show competence in identifying relevant information, defini explaining topics under discussion.CO 2Show competence in working with a methodology, structuring the work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate complete complet	content.											
Course Outcomes (COs):On successful completion of this course, students will be able to (COs):CO 1Show competence in identifying relevant information, define explaining topics under discussion.CO 2Show competence in working with a methodology, structuring the work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate complete complete complete completers.	content.											
Outcomes (COs):On successful completion of this course, students will be able to identifying relevant information, definitionCO 1Show competence in identifying relevant information, definitionCO 2Show competence in working with a methodology, structuring the work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate complete complete complete complete completers.												
(COs):CO 1Show competence in identifying relevant information, define explaining topics under discussion.CO 2Show competence in working with a methodology, structuring the work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate complexity												
CO 1 Show competence in identifying relevant information, define explaining topics under discussion. CO 2 Show competence in working with a methodology, structuring the work, and synthesizing information. Use appropriate registers and vocabulary, and will demonstrate competence in work and synthesizing information.	On successful completion of this course, students will be able to											
CO 1 explaining topics under discussion. CO 2 Show competence in working with a methodology, structuring the work, and synthesizing information. Use appropriate registers and vocabulary, and will demonstrate complete the complete the synthesize of the synthesis of the synthesize of the synthesize of the synthesize												
co 2 explaining topics under discussion. co 2 Show competence in working with a methodology, structuring the work, and synthesizing information. Use appropriate registers and vocabulary, and will demonstrate complete the complete the synthesize of the complete the c	Show competence in identifying relevant information, defining and											
CO 2work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate com												
work, and synthesizing information.Use appropriate registers and vocabulary, and will demonstrate com	Show competence in working with a methodology, structuring their oral											
CO 3 Use appropriate registers and vocabulary, and will demonstrate com												
	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	Demonstrate that they have paid close attention to what others say and can											
respond constructively.												
Develop persuasive speech, present information in a compellin	g, well-											
CO 5 structured, and logical sequence, respond respectfully to opposin	structured, and logical sequence, respond respectfully to opposing ideas,											
show depth of knowledge of complex subjects, and develop their a	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 * * * *												
CO 5 * / / / / / / / / / / / / / / / / / /	*											



Learning strategies, o	contact hou	rs and st	udent lea	rning ti	me			
Learning strategy			Contact I	hours		Stude	nt learning	
						time ((Hrs)	
Lecture			-			-		
Seminar			-		-			
Quiz			-		-			
Small Group Discussion	on (SGD)		14		-			
Self-directed learning	(SDL)		-		-			
Problem Based Learni	ng (PBL)		-		-			
Case Based Learning ((CBL)		-		-			
Clinic			-		-			
Practical			-		-			
Revision		-			-			
Assessment		-			-			
TOTAL		14			-			
Assessment Methods	:							
Formative:					Summa	tive:		
Seminar Topic Selection	on							
Synopsys review								
PPT Review								
Mapping of assessme	nt with Cos	5						
Nature of assessment		CO 1	CO 2	CO 3	CO 4	C	05	
Presentation		*	*	*	*	*		
Feedback Process	• End	-Semeste	r Feedbaa	ck	•	ł		
Reference Material	Particular to	o the chos	sen Semir	nar				



Name of th	e Progran	a:		ME	in Machi	ne Learni	ng							
Course Tit	5				Project Work									
Course Coo		'99		3	Course Instructor:									
Academic					Semester: Second Year, Semesters 3, 4									
No of Cred	its: 25			Prer	Prerequisites: SDLC, communication skills, technical									
				skills	8.									
Synopsis:	The j	project	work a	ims to	ns to challenge the student's analytical and creative									
	abilit	y and to	o allow	the s	the student to synthesize ideas, apply expertise, and									
	insigh	nt learne	d in the	stude	tudent's core discipline.									
	Stude	nts bui	ld self	-confi	dence,	demonstr	ate inde	ependen	ce, and	develop				
	profe	ssionalis	sm on s	uccess	fully co	npletion	of the pr	oject.						
Course														
Outcomes	On su	ccessful	l compl	etion o	of this co	ourse, stu	dents wil	ll be abl	e to					
(COs):														
~ ~ .	Succe	essfully	acquain	t with	with a working environment and processes that are in									
CO 1	place	place at relevant industries.												
CO 2	Famil	iarize w	ith the	challe	nges as r	elevant p	profession	nals.						
CO 3	Revie	w litera	ture and	d deve	op solut	tions for	real time	onboar	d projects	s.				
CO 4	Write	technic	al repor	rt and o	deliver p	oresentati	on.							
CO 5	Apply	engine	ering a	nd mar	management principles to achieve project goal.									
Mapping of	of COs to	Pos												
COs PO	1 PO 2	<i>PO 3</i>	<i>PO</i> 4	<i>PO</i> 5	PO 6	<i>PO</i> 7	PO 8	<i>PO</i> 9	PO 10	PO 11				
CO 1					*	*	*	*	*	*				
CO 2				*										
CO 3 *	*	*	*	*										
CO 4 *	*	*	*											
CO5:					*	*	*	*	*	*				
Course co	ntent and	loutcon	nes:		•	•	·			·				
Content					Compet	encies								
Phase 1:														
Problem	identifi	cation,	sync	opsis	At the e	nd of the	topic stu	ident sh	ould be a	ble to:				
submission	, status	submi	ssion,	mid	d 1. Identify the problem/specification (C1).									
evaluation.					2. Discuss the project (C2).									



^{V3} PIRED BY LIFE (Deen	ed to be University under Section 3 of the UGC	Act, 1956)								
	3. Prepare the outline	(C3).								
	-	n project presentation report								
		(C3).								
		resent mid-term project								
	presentation slides									
	6. Develop projec	-								
		or both in chosen platform								
	(C5).									
Phase 2										
Status submission, final evaluation.	1. Prepare the progres	ss report (C3).								
	2. Prepare the final	project presentation report								
	(C3).	(C3).								
	3. Prepare and presen	nt final project presentation								
	slides (C3, C5).	slides (C3, C5).								
	4. Modify and de	velop implementation in								
	hardware/software	hardware/software or both in chosen platform								
	(C3, C5).									
	5. Justify the method	s used and obtained results								
	(C6).									
Learning strategies, contact hours an	nd 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 Selec	tion		Mid-Term Presentation							
Synopsys review		Second status review								
First status review			Demo & Final Presentation							
Mapping of assessme	ent 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 ch	osen pro	ject						



PROGRAM OUTCOMES (PO) AND COURSE OUTCMES (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	IVICL 603	Applied Linear Algebra	3	*	*	*	*	*	*		*			
4	IVICL 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	IVICE DUSE	Applied Linear Algebra Lab	1	*	*	*	*	*	*					
9		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	MCL 799	Project Work	25	*	*	*	*	*	*	*	*	*	*	*