

Manipal School of Information Sciences

Manipal Academy of Higher Education, Manipal

Outcome Based Education (OBE) Framework

Two Year full time Postgraduate Program

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



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NATURE AND EXTENT OF THE PROGRAM

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

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

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



PROGRAM EDUCATION OBJECTIVE (PEO)

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

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



GRADUATE ATTRIBUTES

S No.	Attribute	Description
		Acquire in-depth knowledge of specific discipline or
	Scholarship of Knowledge	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	Cwitical Thinking	independent judgement for synthesising information to make
2	Critical Thinking	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, design,
4	Research Skill	conduct experiments, analyse and interpret data, demonstrate
7	Research Skin	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	Usaga of madayn 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.
(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 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 own							
7	Project Management	work, as a member and leader in a team, manage projects							
,	and Finance	efficiently in respective disciplines and multidisciplinary							
		environments after consideration of economic 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 author 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							
9	Life-long Learning	to engage in life-long learning independently, with a high							
	Enc-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,							
10	Ethical Practices and	consideration of the impact of research outcomes on							
	Social Responsibility	professional practices and an understanding of responsibility							
		to contribute to the community for sustainable development							
		of society.							
	Independent and	Observe and examine critically the outcomes of one's							
11	Reflective Learning	actions and make corrective measures subsequently and							
	Tenecure Dearning	learn from mistakes without depending on external feedback.							



QUALIFICATIONS DESCRIPTORS

1. Demonstrate:

- (i) systematic, extensive, and coherent knowledge and understanding of machine learning and its applications, and links to related areas/subjects of study; including a critical understanding of the established theories, principles and concepts, and of several advanced and emerging issues in the field of machine learning.
- (ii) procedural knowledge that creates diverse types of professionals related to machine learning, including research and development, teaching, and government and public service.
- (iii) professional communication skills in the domains of machine learning and artificial intelligence including a critical understanding of the latest developments and computing tools.
- Demonstrate comprehensive knowledge about materials, including current research, scholarly, and/or professional literature, relating to essential and advanced learning areas pertaining to machine learning, and techniques and skills required for identifying problems and related issues.
- 3. Demonstrate skills in identifying information needs, collection of relevant quantitative and/or qualitative data drawing on a wide range of sources, analysis and interpretation of data.
- 4. Demonstrate skills in identifying methodologies for formulating evidence-based solutions and arguments.
- 5. Use knowledge, understanding, and skills for critical assessment of a wide range of ideas, complex problems and issues related to machine learning.
- 6. Communicate the results of studies undertaken accurately and unambiguously.
- 7. Address one's own learning needs relating to current and emerging areas of study, making use of research, development, and professional materials as appropriate, including those related to new frontiers of knowledge.
- 8. Apply one's disciplinary knowledge and transferable skills to new/unfamiliar contexts, identify and analyse real-life problems, and seek novel solutions.



PROGRAM OUTCOMES

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

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



11 Independent and Reflective Learning

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





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

FIRST YEAR:

Semester: 1 Semester: 2

Subject Code	Subject Title	L	T	P	C	Subject Code	Subject Title	L	Т	P	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	ı	-	3		Elective - II	3	-	-	3
BDA 602L	Algorithms and Data Structures for Big Data Lab	-	-	3	1	MCL 602L	Advanced Applications of Probability & Statistics Lab	-	-	3	1
MCL 601L	Applied Probability & Statistics Lab	-	-	3	1	MCL 604L	Machine Learning Principles & Applications Lab	-	-	3	1
MCL 603L	Applied Linear Algebra Lab	-	1	3	1	MCL 606L	Deep Learning Lab	-	-	3	1
MCL 605L	Applied Machine Learning Lab	-	1	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 Cree	dits to Award Degree	75				



List of Electives (Theory)

	Elective - 1	Elective - 2			
Code	Subject	Code	Subject		
MCL-615	Applications of Craph Theory		Applied Mathematics for Machine		
MCL-615 Applications of Graph Theory		MCL-616	Learning		
DDA (22	Drive sin Lea of Data Visualization	MCI (47	Natural Language Processing		
BDA-622	Principles of Data Visualization	MCL-617	Principles & Applications		
DD 4 (22	BDA-623 Architecture of Big Data Systems		Convolutional Neural Networks for		
BDA-623			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		
DDA-022L	Principles of Data Visualization Lab	MCL-017L	Principles & Applications Lab		
DDV (331	Architecture of Big Data Customs Lab	MCI 610I	Convolutional Neural Networks for		
BDA-623L	Architecture of Big Data Systems Lab	MCL-618L	Computer Vision Lab		
		ENP-601L	Entrepreneurship		



Name of th	e Progra	m:		ME	in N	Machine	Learnin	g			
Course Tit									for Big I		
Course Co	de:BDA	602		Coi	ırse	Instruc	tor:				
Academic	Year:202	0-2021		Sen	nest	er:First	Year, Se	mester 1			
No of Cred	lits:3			Pre	Prerequisites: Programming in Python, C						
Synopsis:	This	course in	troduce	s sti	uder	nts to e	lementa	ry data	structur	es and d	esign of
	algo	rithms.Stu	idents le	arn	hov	w to de	sign op	timal al	gorithm	s with re	espect to
	time	and space	ce; impl	eme	ement link list, stack, queues, searching and sorting						
	tech	niques, se	ets, trees	s ar	nd g	graphs;	implen	nent str	ing and	l text pr	ocessing
	tech	niques; im	plement	dat	a st	ream alg	gorithm	S.			
Course											
Outcomes	On s	successful	complet	ion	of t	his cour	se, stud	lents wi	ll be abl	e to	
(COs):											
CO 1:	Ana	Analyse recursive programs, solve a general class of recurrence relations.									
CO 2:	Desi	Design programs for implementation of linked lists, stack, queues, binary									
CO 2.	sear	ch tree, so	rting and	d sea	arch	ing.					
CO 3:	Desi	gn progra	ams for	di	ctio	nary, h	ash tal	oles, gi	aphs a	nd short	est path
CO 3.	tech	niques.									
CO 4:	Desi	gn string a	and text	pro	cess	ing pro	grams.				
Mapping	of COs 1	o POs									
COs PO	0 1 PO	2 PO 3	PO 4	PC) 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1 *	*	*							*		
CO 2 *	*	*							*		
CO 3 *	*	*							*		
CO 4 *	*	*	*								
Course co	ntent ar	d outcom	ies:	•		•	•	•	•	-	
Content					Co	mpeten	cies				
Unit 1: Al	gorithm	Specifica	tion and	d A	naly	sis Tec	hnique	s			
Analysis o	Analysis of recursive programs. 1. Define recursive programs (C2)										
Solving re	currence	equations	•		2.	Design	n simple	e recursi	ve prog	rams (C4)
General se	General solution for a large class of 3. Solve recurrence relations (C4)										
recurrence	s.										
Unit 2: El	ementar	y Data St	ructure	S							



(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 Technic	lues
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	<u>I</u>
Construction.	Understand and implement BST and its various
In-order, pre-order and post-order	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 cost
Single source shortest paths and all-	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 Te	chniques
Pattern-Matching Algorithms.	1. Design applications with suitable pattern
Text Compression.	matching algorithms (C4).
Tries.	
Unit 8: Data Stream Algorithms	



Sampling, Random Projection	ns, Basic	1.	Implement	suitable	data	streaming
Algorithmic Techniques			algorithms ((C3).		
Group Testing, Tree Method a	nd Graph					
sketching.						
Learning strategies, contact h	ours and	student	learning tin	ne		
Learning strategy		Conta	ct hours		Student	learning
					time (Hrs	5)
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:				Sumr	native:	
Internal practical Test		Sessional			onal exami	ination
Theory Assignments		End sem			emester examination	
Lab Assignment & Viva			Viva			
Mapping of assessment with	Cos					
Nature of assessment	CO 1	CO 2	CO 3	CO 4		
Sessional Examination 1	*					
Sessional Examination 2		*	*			
Assignment/Presentation				*		
End Semester Examination	*	*	*	*		
Feedback Process • N	Mid-Semes	ster feedb	oack			
• I	End-Semes	ster Feedl	oack			



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								
				Algorithms and Data Structures for Big Data Lab							
				se Instru							
			2021				st Year, So				
No of C				4.00 day 0.0			:Programr				asian af
Synops	SIS:						elementa	•			Ü
		algorith	ıms.Stu	dents l	earn h	ow to c	lesign op	timal al	gorithm	s with re	spect to
		time a	nd spac	e; imp	lemen	t link l	ist, stack	, queue	s, searc	hing and	sorting
		techniq	ues, se	ets, tree	es and	graphs	; implen	nent str	ing and	text pro	ocessing
		techniq	ues; im	plemen	t data	stream a	algorithm	s.			
Course	e										
Outco	mes	On suc	cessful	comple	tion o	f this co	urse, stud	ents wil	l be abl	e to	
(COs):											
CO 1:		Evalua	te the p	erforma	ince of	f algorit	hms.				
CO 2:		Develo	p appli	cations	using	suitable	data stru	ctures.			
CO 3:		Design	applica	itions u	sing d	ata strea	ming and	pattern	matchin	ng algorit	hms.
Mappi	ng of (COs to 1	POs								
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1	*	*	*						*		
CO 2	*	*	*			*					
CO 3	*	*	*		*	*					
Course	e conte	ent and	outcom	es:		•					
Conten	ıt				(Competencies					
Unit 1	Elem	entary l	Data St	ructur	es						
Linked	List,	Stacks,	Queue	s, Sort	ing l	Implement Linked list, Stacks, Queues (C4).					
and Sea	arching	g Techni	ques		I	Design applications using various searching and					
					S	Sorting techniques.					
Unit 2	Tree,	Sets an	d Hash	Table							
Binary Tree, Binary search tree				1	Implement Binary Tree and BST (C4).						
Sets and Hash Tables				I	Design applications using Hash Tables						
Unit 3	Grap	h									
Repres	entatio	n of Gra	ph]	Implement Graph and its traversals (BFS, DFS)					
BFS an	d DFS				((C4).					
					l l						



Shortest path algorithms	I	Design applications with shortest path algorithms				
	((C4).				
Unit 4: Pattern Matching and	Data strea	ming				
	I	mplement patter	n matching a	algorithms (C4).		
Learning strategies, contact he	ours and s	tudent 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:			Summati	ive:		
Internal practical Test			Sessional	al examination		
Theory Assignments			End seme	nester examination		
Lab Assignment & Viva		Viva				
Mapping of assessment with C						
Nature of assessment	CO 1	CO 2		CO 3		
Sessional Examination 1	*	*				
Sessional Examination 2		*	*	•		



Assignment/Presentat	ion	*	*	*		
End Semester Examin	nation	*	*	*		
Laboratory Examinat	ion	*	*	*		
Feedback Process	• N	id-Semester	feedback			
	• E	nd-Semester 1	Feedback			
Reference Material	1. D	ata Structure	s and Algorithms in	Python - Michael T.		
	G	oodrich, Rob	erto Tamassia, and M	lichael H. Goldwasser.		
	Jo	John Wiley & Sons.				
	2. D	ata Streams	s: Algorithms and	Applications - S.		
	M	luthukrishnan	. Foundations and	Γrends in Theoretical		
	C	omputer Scie	nce archive, Volume 1	Issue 2, August 2005,		
	P	ages 117 – 23	6.			



Name of the Program: ME				ME in Machine Learning							
						nd Statistic	es				
_					in Machin						
		ır: 2020-	2021				-	Semester			
No of C								algebra and			
Synop	sis:	This co	ourse ir	itroduc	es fur	ndamenta	l conce	pts in pro	bability	and statis	stics that
		are ess	ential f	or data	scien	ce applica	ations.				
Course	e										
Outco	mes	On suc	cessful	compl	etion	of this co	urse, st	udents wi	ll be abl	e to	
(COs):	:										
CO 1:		Unders	stand ar	nd appl	y the	basic prin	ciples	of samplin	ng.		
CO 2:		Model	randon	n pheno	omena	using ra	ndom v	ariables.			
CO 3:		Calcula	ate & in	nterpret	prob	ability as	a meas	ure of qua	antifying	uncertai	nty.
CO 4:		Constr	uct Bay	esian r	nodel	s for anal	ysing p	ractical p	roblems.	•	
~~ -		Use sa	ample	inform	ation	and per	rform 1	hypothesi	s-test a	nalysis u	ising an
CO 5:		approp	riate st	atistica	l tech	nique to e	explain	attributes	of a pop	oulation.	
Mappi	ing of (COs to 1	Pos								
COs	PO 1	PO 2	PO 3	PO 4	PO S	5 PO 6	PO 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	ies:	<u>l</u>	1	I	1	1	1	1
Conten	ıt					Compete	encies				
Unit 1	: Coun	ting; Pı	obabil	ity Co	ncept	s; Condi	tional I	Probabili	ty		
Multip	lication	n rule	e; po	ermutat	tion;	1. Und	erstand	and appl	y the b	asic princ	ciples of
combination - Sampling: with/without				hout	ut sampling (C1, C3).						
replacement and order matters/does not				not	ot 2. Understand and apply the basic principles of						
matter - Binomial & multinomial				mial	al probability (C1, C3).						
coefficients - Distribution problems					,	3. Differentiate and relate frequency-based					
Set theory; sample space; outcomes;					nes;	es; interpretation of probability to classical					
events - Frequency based definition of			n of	of approach (C4).							



probability - Equally likely vs. not equally likely outcomes - Axioms of probability

Conditional probability; probability tree model; chain rule - Decomposition and the law of total probability - Bayes' rule - intuition, dependence/independence of events.

4. Apply Bayesian principle for modelling practical problems (C5).

Unit 2: Random Variables

Modelling discrete using random variables: Bernoulli, geometric, binomial, negative binomial, hypergeometric, Poisson and distributions - Probability mass function and cumulative distribution function -Expectation and variance: discrete case - Modelling using continuous random variables: uniform, normal, log-normal, exponential, and beta distributions; probability density function Expectation and variance: continuous case - Functions of random variables.

- 1. Understand and differentiate discrete and continuous random variables of practical interest (C2, C4).
- 2. Gain solid foundation in the mathematical aspects of random variables (C2).
- 3. Understand how to use random variables to model random phenomena (C4).
- 4. Compare and contrast practical applicability of random variables (C6).

Unit 3: Sampling and Parameter Estimation

Population and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem – intuition and applications

Point estimation - Standard error - Interval estimation: interpretation of confidence interval - Hypothesis

testing: p-values, significance level and

their interpretations, application to

- 1. Differentiate population and sample (C4).
- 2. Describe population parameters using inferences drawn from a sample (C6).
- 3. Design and apply appropriate hypothesis tests for practical problems (C3).
- 4. Communicate and explain the results of hypothesis testing (C6).



analysis of one- /two-sample n	nean and					
paired data.						
Learning strategies, contact h	ours and	student	learning	time		
Learning strategy		Conto	act 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:					1	
Formative:				Summati	ive:	
Internal practical Test			Sessional examinat			
Theory Assignments				ester examination		
Lab Assignment & Viva			Viva			
Mapping of assessment with	Cos			<u> </u>		
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 • 1	Mid-Semes	ster feed	back			
• I	End-Semes	ster Feed	lback			
Reference Material 1. Introduction to Probability, Charles M. Grinstead, American						
Mathem	atical Soc	iety; 2nd	l Revised	Edition 1997	7. Available online at	



https://open.umn.edu/opentextbooks/textbooks/introduction-to-
probability

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

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



Academic Year: 2020-2021 Sen					Semester:First Year, Semester 1					
No of Credits: 1 Pres					equisites	:MCL 6	501			
Synopsis:	s a ha	nds-on	introdu	ction to	fundam	ental con	cepts in			
	probab	oility an	d statis	stics tha	at are es	sential	for data s	science a	applicatio	ns using
	the R p	orogran	nming 1	anguag	ge.					
Course										
Outcomes	On suc	cessful	compl	etion o	f this co	urse, st	udents wi	ll be abl	e to	
(COs):										
CO 1:	Apply	the bas	ic princ	ciples o	of sampl	ing to p	ractical p	roblems		
CO 2:	Visual	ize prol	bability	conce	pts throu	igh frec	juency-ba	sed inte	rpretation	ıs.
CO 3:	Simula	ite disc	rete ar	nd cont	tinuous	randon	n variable	es for n	nodelling	random
CO 3:	phenoi	mena.								
CO 4:	Design	and ap	ply hy	pothesi	s tests fo	ollowed	by interp	retation	of result	S.
CO 5:	Interpr	et stat	istical	results	and o	commu	nicate th	em una	ambiguou	sly and
CO 5:	effecti	vely.								
Mapping of	COs to	POs								
COs PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1 *	*	*		*						
CO 2	*	*		*						
CO 3 *	*	*	*	*						
CO 4	*	*	*	*	*					
CO 5			*	*	*		*		*	
Course conto	ent and	outcon	ies:		1					
Content				(Compete	encies				
Unit 1: Counting; Probability Concepts; Conditional Probability										
Multiplicatio	n rul	e; p	ermutat	tion;	1. Und	erstand	the bas	ic prin	ciples of	the R
combination	- Samp	ling: w	ith/wit	hout	prog	rammir	ng langua	ge (C1).		
replacement and order matters/does not					2. Develop short code snippets to understand the					
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				
	sample	space;	outcor	mes;	3. Visu	alise a	nd interp	oret pro	bability	concepts



probability - Equally likely vs. not equally likely outcomes - Axioms of probability

Conditional probability; probability tree model; chain rule - Decomposition and the law of total probability - Bayes' rule - intuition, dependence/independence of events.

4. Program and analyse Bayesian models for practical problems (C4).

Unit 2: Random Variables

Modelling discrete using random variables: Bernoulli, geometric, binomial, negative binomial, hypergeometric, Poisson and distributions - Probability mass function and cumulative distribution function -Expectation and variance: discrete case - Modelling using continuous random variables: uniform, normal, log-normal, exponential, and beta distributions; probability density function Expectation and variance: continuous case - Functions of random variables.

- 1. Understand and apply R functions to simulate discrete and continuous random variables (C3).
- 2. Using sampling, compute and interpret different attributes of random variables (C4).
- 3. Visualise and interpret histograms and probability mass/density functions of random variables using state of the art visualisation libraries in R (C4).
- 4. Develop codes to model random phenomena using appropriate random variables (C5).

Unit 3: Sampling and Parameter Estimation

Population and sample - Statistic & sampling distribution - Sample mean and variance - Central limit theorem – intuition and applications

Point estimation - Standard error - Interval estimation: interpretation of confidence interval - Hypothesis testing: p-values, significance level and their interpretations, application to

- 1. Visualise sample data through histograms (C3).
- 2. Compute estimates of population parameters using samples and communicate the uncertainty in the estimates (C4).
- 3. Use R in-built functions for performing hypothesis tests (C4).
- 4. Interpret and communicate the results of hypothesis tests (C6).



analysis of one- /two-sample mea	an and						
paired data							
Learning strategies, contact hou	ırs 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:					1		
Formative:				Summati	ve:		
Internal practical Test			Sessional examinatio				
Theory Assignments			End semester examination				
Lab Assignment & Viva			Viva				
Mapping of assessment with Co	S						
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 • Mic	d-Semes	ster feed	back		1		



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

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



Synop	sis:	This course introduces fundamental concepts in probability and statistics that									stics that		
		are ess	ential fo	or data s	science	applicati	ions.						
Cours	e												
Outco	mes	On suc	On successful completion of this course, students will be able to										
(COs)	:												
CO 1:		Unders	stand ho	w to us	e vecto	ors and m	atrices	to mode	el real-lit	fe quantit	ies.		
CO 2:			Develop a solid understanding of matrix-vector operations and relate them to real-life calculations.										
CO 3:		Apply	and ana	lyse alg	gorithn	ns constru	icted us	ing mat	rix-vecto	or princip	oles.		
CO 4:			Develop models for real-life applications using the least squares technique and interpret the results from a practical perspective.										
CO 5:		Develop a solid foundation for extending matrix-vector principles to modern machine learning algorithms.											
Mapp	ing 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		*	*	*	*	*							
Cours	e conte	ent and	outcom	ies:	l	l .	•	l	1				
Conte	nt				(Competen	cies						
Unit 1	: Vecto	ors											
Conce	ptual	introduc	ction to	o vecto	ors; 1	. Under	stand th	e math	ematical	languag	e behind		
vector	a	ddition;	on; scalar-vector vectors and compare algebraic and geometric										
multip	lication	ı - Do	t produ	ict; no	orm; representations of vectors (C2, C4).								
distanc	ee -	Stan	dard	deviati	ion; 2. Understand mathematical operations involving								
standa	rdizatio	on vs. no	rmaliza	ition; an	igle	vectors and their applications in real-life (C2,							
betwee	en vecto	ors - Ap	plicatio	n exam	ple:	ole: C3).							
k-mea	ns clus	tering a	lgorithi	n - Lin	near 3	3. Consti	ruct a c	lusterin	g algori	thm from	scratch		
depend	lence/ii	ndepend	ence;	basis	-	using vector principles and operations (C5).							



Orthonormal	vectors;	projections;	4.	Gain	a	solid	understanding	of	important
Gram-Schmidt	algorithm.			theore	etica	al princ	ciples to be appli	ed la	ater (C2).

Unit 2: Matrices

Conceptual introduction to matrices; types of matrices (zero, identity, diagonal) - Addition of matrices; transpose; norm - Matrix-vector product - concept & examples - Systems of linear equations: over- & underdetermined systems - Matrix-matrix product - concept & examples - QR factorization - Solving linear equations.

theoretical principles to be applied later (C2).

1. Understand the mathematical language behind

matrices and interpret them as extensions of

- vectors (C2, C6).

 2. Understand mathematical operations involving matrices & vectors and their applications in real-life (C2, C3).
- 3. Gain a solid understanding of important theoretical principles involved in solving systems of linear equations (C2).
- 4. Develop and interpret matrix factorization as a powerful tool for data analysis (C5, C6).

Unit 3: Linear Least Squares

Least squares: problem motivation and examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification

- 1. Understand the mathematical setup of a linear least squares problem using practical examples (C2).
- 2. Formulate linear least squares problem using block matrix operations (C5).
- 3. Understand how to select good features for data fitting using least squares (C2, C6).
- 4. Construct and compare least squares classification with regression (C5, C6).

Learning strategies, contact hours and student learning time

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



Case Based Learning	(CBL)		-			-				
Revision			02			-				
Assessment			06			-				
TOTAL			44			74				
Assessment Methods	S:					I				
Formative:					Summati	ve:				
Internal practical Test	-				Sessional	exan	nination			
Theory Assignments					End seme	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 Examir	nation	*	*	*	*		*			
Feedback Process	• Mic	d-Semes	ster feed	back						
	• End	d-Semes	ster Feed	back						
Reference Material	1. Introdu	ction to	Applie	d Linear	Algebra, Ve	ectors	, Matrices, and			
	Least Squa	ares, St	ephen B	oyd & L	ieven Vande	enberg	ghe, Cambridge			
	University	Press,	1st Edit	ion, 2018	. Available	online	e at http://vmls-			
	book.stanfo	ord.edu/	vmls.pd	f						
	2. Linear	Algebra	and its	Applicat	tions, Gilbert	Stra	ng, CENGAGE			
	LEARNING (RS); 4th Edition, 2005.									
	3. Matrix Methods: Applied Linear Algebra, Richard Bronson and									
	Gabriel B. Costa, Academic Press; 3rd Edition, 2008.									
	4. Matrix	Metho	ds in	Data M	ining and	Patte	rn Recognition			
	(Fundamer	ntals of A	Algorith	ms), Lars	Eldén – Soci	iety fo	or Industrial and			
	Applied M	athemat	tics, 200	7.						

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



No of Credits: 1 Prerequisites:MCL 603									f the UGC Act, 19				
Synops	sis:	This co	urse pr	ovides		ds-on introduction to fundamental concepts in linear							
		algebra	that	are ess	ential	for	dat	a scien	ce applic	ations 1	using the	Python	
		prograi	programming language.										
Course	e												
Outco	mes	On successful completion of this course, students will be able to											
(COs):													
CO 1:		Develop solid skills in using Python's legacy libraries for coding matrix-vector operations											
CO 2:		Implen	nent alg	gorithm	s cons	struct	ed ı	ısing m	atrix-vect	or princ	iples.		
CO 3:		Implement models for real-life applications using the least squares technique and interpret the results from a practical perspective.									echnique		
Mapping of COs to Pos													
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PC	6	PO 7	PO 8	PO 9	PO 10	PO 11	
CO 1	*	*											
CO 2		*	*	*	*								
CO 3	*	*	*	*	*	*							
Course	e conte	nt and	outcon	ies:				l				<u>I</u>	
Conten	ıt					Competencies							
Unit 1	Vecto	ors											
Concep	otual i	introduc	tion t	o vec	tors;	1. U	Jnd	erstand	how to p	erform	vector of	perations	
vector	ac	dition;	sc	alar-ve	ector	using Python (C2).							
multipl	ication	- Do	prod	uct; no	orm;	2. V	⁷ isu	alize v	vectors a	nd relat	te them	to their	
distanc	e -	Stan	dard	deviat	tion;	9	eor	netric d	escription	(C1, C	2).		
standar	dizatio	n vs. no	rmaliza	ation; a	ngle	3. I	mpl	lement t	the K-mea	ns algor	rithm fron	n scratch	
betwee	between vectors - Application example: using vector operations (C5).												
k-mear	ns clus	tering a	lgorith	m - Li	near	4. I	mpl	lement	and inte	rpret th	e output	of the	
depend	lence/ir	ndepend	ence;	basis	-	(Grar	n-Schm	nidt algori	thm (C5).		
Orthon	ormal	vecto	ors; p	orojecti	ons;								
Gram-S	Schmid	lt algorit	hm.										
Unit 2	Matri	ices											



Conceptual introduction to matrices;
types of matrices (zero, identity,
diagonal) - Addition of matrices;
transpose; norm - Matrix-vector product
- concept & examples - Systems of
linear equations: over- & under-
determined systems - Matrix-matrix
product – concept & examples - QR
factorization - Solving linear equations.

- 1. Understand how to perform matrix operations using Python (C2).
- 2. Implement and interpret matrix-vector operations using block-matrix operations (C5).
- 3. Understand how to solve linear systems of equations using Python (C2).
- 4. Code practical applications of QR factorization of matrices (C4).

Unit 3: Linear Least Squares

Least squares: problem motivation and examples - Solving linear least squares problems - Least squares data fitting; validation; feature engineering - Least squares classification

- 1. Solve linear least squares problems using Python and interpret the results (C3).
- 2. Implement and fine-tune feature extraction using least squares for practical problems (C5).
- 3. Implement least squares classification (C3).

Learning strategies, contact hours and student learning time

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

Assessment Methods:



Formative:			Summative:						
Internal practical Test		Sessional examination							
Theory Assignments			End semester examination						
Lab Assignment & V	iva				Viva				
Mapping of assessme	ent with Co	S			l				
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-Seme	ster feed	back					
	• End	d-Semes	ster Feed	lback					
Reference Material	1. Introdu	ction to	Applie	d Linear	Algebra, Ve	ctors, Matrices, and			
	Least Squa	ares, St	ephen B	Boyd & L	ieven Vande	nberghe, Cambridge			
	University	Press,	1st Edit	ion, 2018	. Available o	online at http://vmls-			
	book.stanf	ord.edu/	/vmls.pd	lf					
	2. Linear	Algebra	a and its	Applicat	ions, Gilbert	Strang, CENGAGE			
	LEARNIN	G (RS)	; 4th Edi	tion, 2005	5.				
	3. Matrix Methods: Applied Linear Algebra, Richard Bronson and								
	Gabriel B. Costa, Academic Press; 3rd Edition, 2008.								
	4. Matrix Methods in Data Mining and Pattern Recognition								
	(Fundamer	ntals of	Algorith	ms), Lars	Eldén – Soci	ety for Industrial and			
	Applied M	athema	tics, 200	7.					

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



Synop	sis:	This course provides a broad introduction to important concepts and algorithms										
		in appl	ied mac	chine le	arnin	ıg.						
Cours	e											
Outco	mes	On successful completion of this course, students will be able to										
(COs)	:											
CO 1:			Develop practical experience with state-of-the-art machine learning tools and libraries.									
CO 2:		Differentiate between different types of machine learning paradigms and choose an appropriate one for a given application problem.									gms and	
CO 3:			Apply different types of supervised and unsupervised machine learning algorithms to practical problems and assess their performance.								learning	
CO 4:		Understand the importance of feature engineering in machine learning applications.								learning		
CO 5:		Acquire a solid foundation in basic machine learning skills for more advanced expositions.								ndvanced		
Mapp	ing 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	*	*	*	*						*		
Cours	e conte	ent and	outcom	ies:				•	•	1	•	
Conte	nt					C	ompeter	icies				
Unit	1: Intr	oductio	n to N	Aachin	e Le	ar	ning; I	ntroduc	ction to	Super	rvised L	earning;
Decisi	on Tre	es										
Overv	iew of S	Supervis	sed (regi	ression	and	d 1. Gain a basic understanding of different types of						
classif	ication)	, unsup	supervised (clustering problems and nomenclature in machine									
and d	imensio	ionality reduction), semi- learning (C2).										
superv	ised, a	nd reinf	orceme	nt learn	ing	2.	Under	stand a	and int	terpret	results o	of cross
with	practica	actical examples - Machine validation in machine learning through a simple								a simple		
	algorithm (C2, C3).											



learning nomenclature: raw data, types of features and outputs, feature vector.

Computing distances and similarities -Prototype based classification - Knearest neighbours - Over- and underfitting -Introduction to cross validation

Decision tree model of learning -Classification and regression using decision trees - Splitting criteria: entropy, information gain, Gini impurity - Building a decision tree

- 3. Understand the decision tree learning model and splitting criteria (C2).
- 4. Compare and contrast classification vs regression using decision trees (C4).

Unit 2: Linear Models; Feature Selection; Introduction to Unsupervised Learning

Linear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance trade-off - Regularized linear regression

Filter, wrapper, and embedded methods

Clustering vs. classification -Hierarchical clustering: dendogram construction, types of linkage -Dimension reduction using principal component analysis (PCA)

- 1. Understand the basics of linear models for regression and classification, interpret results and coefficients (C4).
- 2. Differentiate feature selection approaches in machine learning (C4).
- 3. Understand the working principle behind hierarchical clustering (C2).
- 4. Visualize the mathematical setup behind PCA and compare the matrix-factorization vs. projection-error-minimisation approaches (C4, C5).

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



Probabilistic modelling of data using
parameters - Introduction to maximum
likelihood estimation (MLE) of
parameters - Naive Bayes model for
classification - Logistic regression for
binary classification

Classification using linear SVM - Dealing with nonlinearly separable data

Bagging: classification using random forest - Boosting

- 1. Formulate maximum likelihood estimation of model parameters (C5).
- Understand the probabilistic principles behind Naive Bayes and Logistic Regression algorithms (C2).
- 3. Formulate the SVM mathematical model and interpret algorithm parameters and results (C5).
- 4. Develop intuition and ideas behind ensemble algorithms for machine learning (C5).

Learning strategies, contact hours and student learning time

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

Assessment Methods:

Formative:				Summative:			
Internal practical Test				Sessional examination			
Theory Assignments				End semester examination			
Lab Assignment & Viva				Viva			
Mapping of assessment with Cos							
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5		
Sessional Examination 1	*	*					



Sessional Examinatio	n 2		*	*	*						
Assignment/Presentat	ion	*	*	*	*	*					
End Semester Examin	nation	*	*	*	*	*					
Feedback Process	Mid-Semester feedback										
	• End	d-Seme	ster Feed	lback							
Reference Material	1. Grokkii	1. Grokking Machine Learning, Luis G. Serrano, Manning									
	Publication	ns; 1st I	Edition, 2	2019.							
	Online r	Online resource from Manning Publications available at									
	https://ww	w.manı	ning.com	/books/g	rokking-machii	ne-learning					
	2. A Cour	se in M	Iachine 1	Learning	, Hal Daumé II	I – Online resource					
	available a	t http://	ciml.info	0/							
	3. An Inti	oduction	on to St	atistical	Learning with	Applications in R,					
	Gareth Jan	nes, Da	niela W	itten, Tre	evor Hastie and	Robert Tibshirani,					
	Springer; 1	st Edit	ion, 2013	3, Corr. 7	th printing 201	7 Edition.					
	4. Mathen	natics fo	or Machi	ne Learn	ing, Marc Peter	Deisenroth, A Aldo					
	Faisal, and	d Chen	g Soon	Ong –	Online resourc	e from Cambridge					
	University	Press	available	e at http	s://mml-book.g	thub.io/book/mml-					
	book.pdf.										

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



Synops	sis:	This c	ourse p	rovides	a cod	ing-based	introdu	action to	o impor	tant conc	epts and	
		algorit	hms in a	applied	machi	ne learnir	ig using	Python				
Course	e											
Outcor	mes	On suc	ccessful	comple	tion of	f this cou	se, stuc	lents wi	ll be abl	e to		
(COs):												
CO 1:		Develo	op codes	s using	state o	f the art n	nachine	learning	g tools a	ınd librari	es.	
CO 2:		Code	lifferent	types	of macl	hine learn	ing para	adigms a	and cho	ose an app	propriate	
002.		one for a given application problem.										
CO 3:		Code different types of supervised and unsupervised machine learning										
		algorithms to practical problems and assess their performance.										
CO 4:		Impler	Implement and explore feature engineering approaches in machine learning									
CO 4.		applica	applications.									
CO 5:		Acquii	e a soli	d found	lation i	in coding	skills f	or more	advanc	ed applica	ations of	
CO 3.		machine learning.										
Mapping of COs to POs												
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	
CO 1	*		*	*	*							
CO 2	*	*	*	*	*							
CO 3	*	*	*	*	*	*		*				
CO 4		*	*	*	*	*				*		
CO 5	*	*	*	*	*				*			
Course	e conte	ent and	outcom	ies:								
Conten						Competen						
			on to N	Machin	e Lea	rning; I	ntroduo	ction to	Super	vised Lo	earning;	
Decisio	on Tre	es										
Overvi	ew of S	Supervis	sed (regi	ression	and 1	l. Progra	ım da	ta, pei	rform	data wi	rangling,	
), unsup			_	unders	stand th	e data	matrix,	and diff	erentiate	
and di	mensio	onality	reducti	on), se	mi-	betwee	en samp	ole and f	eature (C2, C4).		
supervi	ised, a	nd reinf	orceme	nt learn	ing 2	2. Invest	igate o	ver- ar	nd unde	erfitting	concepts	
with p	oractica	al exan	nples -	Mach	ine	using	the K-n	earest n	eighbou	r algorith	m (C3).	
learnin	g nom	enclatur	e: raw	data, ty	pes 3	3. Implei	ment a	nd inte	erpret r	results of	f cross-	
of featu	ures and outputs, feature vector. validation (C3).											



Computing distances and similarities -Prototype based classification - Knearest neighbours - Over- and underfitting -Introduction to cross validation 4. Implement decision tree models in Python, fine-tune model parameters, and interpret results (C4).

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 Selection; Introduction to Unsupervised Learning

Linear model for regression and classification - Simple linear regression: model, estimation and interpretation of coefficients - Introduction to bias/variance trade-off - Regularized linear regression

Filter, wrapper, and embedded methods

Clustering vs. classification Hierarchical clustering: dendogram
construction, types of linkage Dimension reduction using principal
component analysis (PCA)

- 1. Implement linear models in Python and interpret model coefficients for practical problems.
- 2. Implement and visualize bias-variance tradeoff using linear regression as a basis (C4).
- 3. Compare, and contrast different feature engineering approaches for practical problems (C4).
- 4. Visualize the output of hierarchical clustering and PCA algorithms and interpret the results (C4).

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

Probabilistic modelling of data using parameters - Introduction to maximum likelihood estimation (MLE) of

1. Implement maximum likelihood estimation for a simple model (C4).



Cheemen to or	e University under Section 3 of the UGO	7716, 1750)		
parameters - Naive Bayes model for	2. Analyse the peri	formance	of the Naive Bayes	
classification - Logistic regression for	model for practic	al probler	ms (C4).	
binary classification	3. Apply the SVM a	lgorithm	for linearly- and not-	
	linearly separa	ıble dat	ta, compare the	
Classification using linear SVM -	performance (C5).		
Dealing with nonlinearly separable data	4. Through coding	, underst	and how ensemble	
	methods in mach	ine learnii	ng work (C3).	
Bagging: classification using random				
forest - Boosting				
Learning strategies, contact hours and	student learning tim	ie		
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:		Summativ	ve:	
Internal practical Test	5	Sessional 6	examination	
Theory Assignments]	End semester examination		
Lab Assignment & Viva	,	Viva		
Mapping of assessment with Cos	I			



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-Seme	ster feed	back		<u> </u>				
	• End	l-Semes	ster Feed	back						
Reference Material	1. Grokkir	1. Grokking Machine Learning, Luis G. Serrano, Manning								
	Publication	Publications; 1st Edition, 2019.								
	Online resource from Manning Publications available at									
	https://www	v.mann	ing.com	/books/gro	okking-machine-l	earning				
	2. A Cours	se in M	achine I	earning,	Hal Daumé III –	Online resource				
	available at	http://d	ciml.info	/						
	3. An Intr	oductio	n to Sta	tistical L	earning with Ap	plications in R,				
	Gareth Jam	nes, Da	niela Wi	tten, Trev	or Hastie and Ro	bert Tibshirani,				
	Springer; 1	st Editi	on, 2013	, Corr. 7tl	printing 2017 Ed	dition.				
	4. Mathem	atics fo	r Machii	ne Learnin	g, Marc Peter Dei	isenroth, A Aldo				
	Faisal, and	Cheng	g Soon	Ong – O	nline resource fi	rom Cambridge				
	University	Press	available	at https:	//mml-book.githu	ıb.io/book/mml-				
	book.pdf.									

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



Synop	sis:	This course introduces basic graph theoretic concepts and some applications in										
		machin	ne learn	ing.								
Cours	e											
Outco	mes	On suc	cessful	comple	tion	of	this cour	se, stud	ents wi	ll be abl	e to	
(COs)	:											
CO 1:			-	_			_		•	aph theo	retic cond	cepts and
							practical					
CO 2:		Apply	Apply appropriate algorithms for solving graph theoretical problems.									
CO 3:		Relate a real-life problem to an appropriate graph theoretic setup.										
CO 4:		Describe how graph theory can be used for machine learning applications.										
CO 5:	Compare and contrast applications of graph theory to small and big data.											
Mapping of COs to POs												
COs	PO 1	PO 2	PO 3	PO 4	PO	5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1	*											
CO 2	*	*	*									
CO 3	*	*	*									
CO 4		*	*	*			*				*	
CO 5		*	*	*						*		
Cours	e conte	ent and	outcom	ies:			l	l		l		
Conte	nt					C	ompeten	cies				
Unit 1	: Grap	hs; Eul	er Tou	rs and l	Ham	ilto	on Cycle	es				
Graph	s and	their	represe	ntations	; -	1.	Under	stand ba	sic con	ponents	s of a gra	ph (C2).
Incide	nce an	d adja	cency	matrice	s -	2.	Under	stand, o	compare	and c	ontrast i	ncidence
Vertex	degree	es - Path	s and co	onnectio	on -		and ad	jacency	matrice	es (C2, C	C5).	
Cycles	s - Dire	ected gr	aphs -	Subgra	phs	3.	Under	stand tl	ne prac	tical ap	plication	s of the
and si	upergra	phs - '	The sho	ortest p	ath		traveli	ng sales	sman pr	oblem (C3).	
proble	m - Fo	rests ar	nd trees	, Cayle	y's							
formu	la.											
The tra	aveling	salesma	an probl	em.								
Unit 2	: Flow	in Netv	vorks;N	Iatchin	ıgs; (Col	louring 1	Probler	ns			
Flows	and c	uts - N	Max-flo	w min-	cut	1.	Visual	ize ne	twork	flow p	roblems	through
theore	m and i	ts appli	cations.				applica	ations (C3).			
<u> </u>												



		2. Und	lerstand	matching	proble	ems	and	their
Matchings and coverings in bipa	artite	prac	tical app	lications (C	3).			
graphs - Perfect matchings		3. Und	lerstand	edge &vertexcolouring and their				
Applications of matchings.		practical applications (C3).						
Edge colouring& Vertex colouring	,							
Unit 3: Random walks and Appli	cation	s; Spect	ral Clus	tering and	Applic	ation	ıs	
		1. Und	lerstand	random wa	alks aı	nd its	s pra	ctical
		app]	lications	(C3).				
		2. Mod	del mult	idimension	al data	a as	simi	larity
		grap	oh (C4).					
		3. Und	lerstand s	spectral clus	stering	and i	ts pra	ctical
		app]	lications	(C3).				
Learning strategies, contact hour	s and	student	learning	g time				
Learning strategy		Contact hours			Student learning		rning	
					time	e (Hr.	s)	
Lecture		30	30			60		
Quiz		02			04	04		
Small Group Discussion (SGD)		02			02	02		
Self-directed learning (SDL)		-			04	04		
Problem Based Learning (PBL)		02			04	04		
Case Based Learning (CBL)		-			-	-		
Revision		02			-			
Assessment		06			-			
TOTAL		44			74			
Assessment Methods:					l.			
Formative:				Summa	tive:			
Internal practical Test				Sessiona	al exan	ninati	on	
Theory Assignments		End semeste			nester e	xami	natio	n
Lab Assignment & Viva			Viva	Viva				
Mapping of assessment with Cos								
Nature of assessment	CO 1	CO 2	CO 3	CO 4		СО	5	



Sessional Examinatio	Sessional Examination 1								
Sessional Examinatio		*	*	*					
Assignment/Presentat	*	*	*	*	*				
End Semester Examin	*	*	*	*	*				
Feedback Process	Mid-Semester feedback								
	End-Semester Feedback								
Reference Material	1. Introdu	ction to	Graph T	Theory, F	Richard J. Tru	udeau, Dover			
	Publica	tions Ir	nc.: 2nd F	Revised I	Edition, 1994	ł.			
	2. Pearls i	n Grap	h Theory	: A Com	prehensive I	ntroduction, Nora			
	Hartsfi	eld and	Gerhard	Ringel,	Dover Public	cations,2003.			
	3. Graph Theory, Adrian Bondy, M. Ram Murty, Springer								
	Publica	tions,1	st Editior	n, 2008.					

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



Synop	sis:	This course provides a practical introduction to understanding, visualizing, and												
Бушор	5254		_		_	ic conce				_	8,			
Cours	e		0 0 0 0 0 0	0-"P"			P1							
Outco		On suc	ccessful	comple	etion of	this cou	rse, stud	lents wi	ll be abl	le to				
(COs)		on suc	0000101	Compre			iso, stat	ZOIILE WI	n o c do.					
CO 1:	•	Visual	Visualize graphs and graph models using Python.											
CO 2:		Implement appropriate algorithms for solving graph theoretical problems.												
CO 3:		Implement graph theoretic approaches for machine learning applications.												
	ing 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	*	102	103	104	103	100	107	100	109	1010	1011			
CO 2	*	*	*		*									
CO 3	*	*	*		*									
	o conto	nt and	outcom	000										
Course content and outcomes: Content Competencies														
		ha Eul	on Tour	a and l		_								
						Viene		aha nain	a Dutha	n (C2)				
•			represei			. Visua		-			a ayah aa			
			cency r							s of graph				
			ns and co			connectivity using the adjacency matrix (C3).								
•			aphs —		•									
		-	The sho	-										
formul		oresis a	nd trees	, Cayle	ey s									
		colocmi	on neobl	am										
			an probl		ogg. Co	Jourina	Duahlar	ma						
			Max-flo			louring			flow	robloma	through			
				W IIIIII-	-cut 1				now p	roblems	uirougn			
theore	in and i	ts appli	cations.				ations (o nnli cot	ions of n	actohina			
Motob	inge er	ad cove	rings i	n hine:	tite 2	_	_			ions of n	iatennig,			
	-		erings i	-	ine	euge a	x vertex	colourir	ig (C3).					
graphs		Perfect		chings	-									
Appno	anons	of matcl	mngs.											



Edge colouring& Vertex colouring.						
Unit 3: Random Walks and Application	ons; Spectral Clust	tering and A	Applications			
	 Create a random walk and analyse its properties (C4). Model multidimensional data as similarity graph (C4). Apply spectral clustering to practical problems (C3). 					
Learning strategies, contact hours and		time	Tarana a a			
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:		Summati	ve:			
Internal practical Test		Sessional	examination			
Theory Assignments		End seme	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 Examinatio	*	*				
Sessional Examinatio			*	*		
Assignment/Presentat	ion	*	*	*	*	*
Laboratory examinati	on	*	*	*	*	*
Feedback Process Reference Material	 End Introdu Publica Pearls i Hartsfie Graph 	d-Semestion to tions In Grapheld and Theory,	c.: 2nd R Theory: Gerhard	back Theory, Rid Revised Ed A Compt Ringel, Do Bondy, M.	chard J. Trudeau, lition, 1994. rehensive Introdu overPublications, Ram Murty, Spr	action, Nora ,2003.

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



No of C	No of Credits: 3 Prerequisites: Programming in Python													
Synop	sis:	This co	ourse pr	ovides	insigh	tht on data visualization, the art and science of turning								
		data in	to reada	able gra	aphics	s; design and create data visualizations based on data								
		availab	ole and	tasks t	to be a	achieved; data extraction, data modelling and data								
		proces	sing; n	nap dat	a attri	butes to	graphi	cal attrib	utes, and	d strategi	c visual			
		encodi	ng base	d on k	nown j	propertie	s of vis	ual percep	otion.					
Cours	e													
Outco	mes	On suc	cessful	compl	etion o	of this co	ourse, st	udents wi	ll be abl	e to				
(COs)	Os):													
CO 1:		Extrac	ttransfo	rms an	d store	e data fro	m vari	ous data s	ources.					
		Unders	Understand the key techniques and theory used in visualization, including data											
CO 2:		models	s, grap	d tech	niques fo	or visua	al encod	ing and						
		interac	tion.											
CO 3:		Work with several common data domains and corresponding analysis tasks.												
CO 4:		Build and evaluate visualization systems.												
CO 5:		Read a	nd disc	uss res	earch	papers fi	om the	visualizat	ion liter	ature.				
Mappi	ing 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	*	*	*	*										
Cours	e conte	ent and	outcon	ies:		'	•	1		1				
Conte	ıt					Compet	encies							
Unit 1	: Intro	duction	to We	b Scra	ping									
Web so	craping	models	and te	chnique	es,	1. Und	erstand	ing variou	s forma	ts of data	. (C1)			
Case	study:	Beauti	fulSou	p, Scr	apy,	2. Desi	gn pro	grams to	dynamio	cally exti	act data			
Seleniu	ım					fron	web. (C4)						
						3. Desi	gn prog	grams to re	ead data	from vari	ous data			
						sour	ces. (C	4)						
Unit 2	Unit 2: Data Analysis													



Data	structures	for	analys	is:	numpy,
panda	as				
D-4-	337		71	т	

Data Wrangling: Clean, Transform, Merge, Reshape

Data Aggregation and Group Operations

Case study: Exploratory analysis of public / scrapped datasets

- 1. Understand and integrate various data structures for data analysis process (C2).
- 2. Create various techniques to clean and handle missing data (C4).
- 3. Design data filtering and transformation techniques (C4).

Unit 3: Data Visualization

Data Visualization – classification, infographics versus data visualization, visualization for supporting exploratory data analysis, visual art, choosing appropriate visual encodings, rules for visualization - Visualization techniques: time series, statistical distributions, maps - Data visualization for web

- Describe what is the purpose of Visualization.
 (C2)
- 2. Describe several ways of classifying visualization. (C2)
- 3. Explain what explorative and explanative visualization is. (C2)
- 4. Differentiate data visualization and visual art. (C2)
- 5. Create visualization for time series data. (C4)
- 6. Create visualization for statistical distributions.(C4)
- 7. Create visualization for maps, Hierarchical data and network data. (C4)

Learning strategies, contact hours and student learning time

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



Revision			02			-	
Assessment			06			-	
TOTAL				74			
Assessment Methods	5:	<u>.</u>					
Formative:		Summative	:				
Internal practical Test					Sessional ex	aminat	ion
Theory Assignments					End semeste	r exam	ination
Lab Assignment & V	iva				Viva		
Mapping of assessme	ent with Co	OS					
Nature of assessment	CO 1	CO 2	С	CO 4		CO 5	
				3			
Sessional Examinatio	n 1	*	*				
Sessional Examinatio	n 2			*	*		
Assignment/Presentat	ion	*	*	*	*		*
End Semester Examir	nation	*	*	*	*		*
Laboratory examinati	on	*	*	*	*		*
Feedback Process	• Mi	d-Semeste	er feedbac	k	1		
	• En	d-Semeste	r Feedbac	ck			
Reference Material	1. Websi	te Scrapi	ing with	Py	thon: Using	Beaut	ifulSoup and
	Scrap	y, Gábor &	kHajba, A	PRE	ESSPublication	ns, 1 st E	Edition, 2018.
	2. Web S	Scraping	with Pyt	hon:	Collecting N	Aore D	Oata from the
	Moder	rn Web, R	Shroff, O'Reil	ly, 2 nd	Edition, 2018.		
	3. Design	ning Data	atio	ns, Julie Steel	le and	Noah Iliinsky;	
	O'Reil	ly Media;	1 st Edition	n, 20	11.		
	4. Pythor	n for Data	Analysi	s, W	.McKinney; O	'Reilly	; 2 nd Ed, 2018.

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



Acaden	Academic Year:2020-2021 Semester: First year, Semester 1											
No of C	Credits:	1				erequisites: Programming in Python						
Synops	sis:	Thi	s cours	e provi	des i	insi	nsight on data visualization, the art and science of					
		turi	ning da	ta into 1	reada	abl	e graphi	ics; des	ign and	create d	ata visua	lizations
		bas	ed on	data av	ailab	ole	and tas	ks to b	e achiev	ed; data	a extracti	on, data
		mo	delling	and dat	a pro	oce	essing; n	nap dat	a attribut	tes to gra	aphical at	tributes,
		anc	l strate	gic vis	ual	en	coding	based	on kno	wn proj	perties o	f visual
			ception	_			C					
Course												
Outco		On suc	cessful	comple	tion	of	this cou	rse, stu	dents wi	ll be abl	e to	
(COs):		011 500	•••	· ompre		-		150, 500				
CO 1:		Scrape data from different data sources.										
CO 2:		Clean, analyse, and transform data.										
CO 3: Visualize data using different techniques, tools and charts.												
		COs to 1									1	1
COs	PO 1	PO 2	PO 3	PO 4	PO	5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1	*	*	*		*					*	*	
CO 2	*	*	*		*		*		*	*	*	
CO 3	*	*	*	*	*		*		*		*	
Course	e conte	ent and	outcom	es:								
Conten	ıt					C	ompeter	ncies				
Unit 1	Data	Scrapp	ing									
Web so	rappin	g model	S			1.	Identif	y differ	ent types	of data	sources ((C2).
Installi	ng an	d conf	iguring	tools	to	2.	Design	applica	ations to	scrap sta	atic data ((C4).
handle	differe	ent data	types.			3.	Design	appli	cations	to ext	ract dat	a from
							dynar	nic web	pages (C4).		
Unit 2	Data	Analysi	s			<u> </u>						
Workin	ng wit	h packa	ages lik	ke num	ру,	1.	Design	script	s to cle	an, han	dle missi	ing data
pandas	, skleaı	rn					(C4).					
Perform	n explo	oratory o	lata ana	lysis.		2.	Design	scripts	to apply	require	d transfo	rmations
							to cle	aned da	ıta (C4).			
Unit 3	Data	Visuali	zation			<u> </u>						
	Chit 3. Data Visualization											



Creating different types	of	1. I	Develop appli	cations	for exploratory data		
Visualization.			visualization (1 ,		
Creating different types of charts.			`	ŕ	ate static visualization		
, , , , , , , , , , , , , , , , , , ,							
		using various visual encodings (C4). 3. Create dynamic visualization for web (C4).					
Learning strategies, contact hou	ırs and						
Learning strategy			ontact hours		Student learning		
0 07					time (Hrs)		
Lecture		1:	2		-		
Seminar		+-			-		
Quiz		+-			-		
Small Group Discussion (SGD)		+-			_		
Self-directed learning (SDL)		+-			-		
Problem Based Learning (PBL)		+-					
Case Based Learning (CBL)		0:	3				
Clinic		_					
Practical		2.	4		_		
Revision		0:			_		
Assessment		0					
TOTAL		4		-			
TOTAL					-		
Assessment Methods:							
Formative:				Summa	ativo.		
Internal practical Test					al examination		
-							
Theory Assignments					nester examination		
Lab Assignment & Viva				Viva			
Marriag of aggresses 4 24 C							
Mapping of assessment with Co			00.2		CO 2		
Nature of assessment	CO 1		CO 2		CO 3		
0 1 1 1 2 1 1	ale.						
Sessional Examination 1	*						



Sessional Examinatio	n 2		*	*						
Assignment/Presentat	ion	*	*	*						
End Semester Examir	nation	*	*	*						
Laboratory Examinati	on	*	*	*						
Feedback Process	• Mi	id-Semes	ster feedback	1						
	• En	End-Semester Feedback								
Reference Material	1. Websi	ite Scra	ping with Pyth	on: Using BeautifulSoup and						
	Scrap	y, Gábor	&Hajba, APRES	SPublications, 1 st Edition, 2018.						
	2. Web	Scraping	g with Python: (Collecting More Data from the						
	Mode	rn Web,	Ryan Mitchell Sh	nroff, O'Reilly, 2 nd Edition, 2018.						
	3. Desig	ning Dat	ta Visualizations	s, Julie Steele and Noah Iliinsky;						
	O'Reil	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 in Machine Learning					
Course Title:	Architecture of Big Data Systems					
Course Code: BDA 623	Course Instructor:					
Academic Year:2020-2021	Semester: First Year, Semester 1					



No of Credits: 3 Prerequisites: Programming in Python, Java													
Synopsis:	This C	ourse p	rovides	insi	ght	on con	cept of	big data	charact	eristics, b	atch and		
	lambda	a archit	ecture;	basi	c i	file syst	ems ir	n Big D	ata; cor	ncepts of	Hadoop		
	framev	vork, S ₁	oark fra	mew	vor	k and th	neir inte	ernals; N	/Iap-redu	ace progr	amming,		
	Spark	progran	nming;	diffe	ren	t layers	with us	se cases	demonst	trations.			
Course													
Outcomes	On suc	cessful	comple	this cou	rse, stu	dents wi	ll be abl	e to					
(COs):	Os):												
CO 1:	Exami	Examine the type of data in big data.											
CO 2:	To des	ign app	lication	s bas	sed	with Ha	adoop f	ramewo	rk.				
CO 3:	To des	ign app	lication	s bas	sed	with sp	ark arc	hitecture					
CO 4:	To bui	ld appli	cations	base	d o	n the Bi	g Data .	Architec	ture plat	forms and	d analyse		
CU 4:	the results based on the outcome of the applications used.												
Mapping of COs to POs													
COs PO 1	PO 2	PO 3	PO 4	PO	5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11		
CO 1 *	*	*				*							
CO 2 *	*	*		*			*			*			
CO 3 *	*	*		*			*			*			
CO 4 *	*	*		*		*	*			*			
Course cont	ent and	outcom	ies:	•					•				
Content					C	ompeter	ncies						
Unit 1: Clas	sifying I	Big Data	a Chara	actei	rist	cics							
Analysis type	e - real ti	ime or l	atched	for		1. Id	entify o	different	types of	Data			
later analysis					2. Identify processing methodology								
Processing 1	nethodol	logy -	predicti	ive,									
analytical, ac	l-hoc que	ery, and	reporti	ng.									
Data frequen	cy and si	ize											
On dem	and, as	with so	cial me	edia									
data													
Continue	ous fee	ed, re	al-time	-									
weather data	, transact	tional da	ata										
Time ser	ries - tim	e-based	data										



be University under Section 3 of the UGC Act, 1936/
bda architecture
1. Understand Lambda architecture to handle
Big Data (C2).
2. Understand different layers in Lambda
Architecture (C2).
d Speed Layer
1. Develop applications to store data in HDFS
(C4).
2. Develop applications for batch processing
using Map Reduce technique (C4).
3. Understand the need of serving layer (C2).
4. Design application to store data for
processing in serving layer (C4).
5. Understand the need of Speed layer for data
processing (C2).
luce
1. Understand Spark Architecture for data
processing (C2).



DataFrame	2. Design a	applications using DataFrames and
Transformations and Actions	RDDs (0	C4).
Spark SQL		
Resilient Distributed Datasets		
(RDDs)		
Unit 5: Stream Processing using Spark		
Advantages and challenges of stream	1. Understa	and different stream processing
processing	techniqu	nes (C2).
Stream Processing Design Points	2. Design a	applications for handling real time
Streaming APIs	data usir	ng Structured Streaming (C4).
Structured Stream Processing		
Unit 6: Machine Learning using Spark		
High level M-Lib concepts	1. Understa	and different libraries and packages
M-Lib in Action	for mach	nine learning in Spark (C2).
	2. Design	machine learning model using
	Spark (C	C4).
<u> </u>	• ,	'
Learning strategies, contact hours and	•	·
Learning strategies, contact hours and Learning strategy	•	g time
	student learnin	g time
	student learnin	g time Student learning
Learning strategy	student learnin Contact hours	g time Student learning time (Hrs)
Learning strategy Lecture	student learnin Contact hours 30	s Student learning time (Hrs) 60
Learning strategy Lecture Quiz	student learnin Contact hours 30 02	g time Student learning time (Hrs) 60 04
Lecture Quiz Small Group Discussion (SGD)	student learnin Contact hours 30 02 02	g time Student learning time (Hrs) 60 04 02
Lecture Quiz Small Group Discussion (SGD) Self-directed learning (SDL)	student learnin Contact hours 30 02 02 -	Student learning time (Hrs) 60 04 02 04
Lecture Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL)		Student learning time (Hrs) 60 04 02 04 04 04 04 04 0
Lecture Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL)		Student learning time (Hrs) 60 04 02 04 04 04 -
Lecture Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Revision	Contact hours 30	Student learning time (Hrs) 60 04 02 04 04 - - -
Lecture Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Revision Assessment	Contact hours 30	Student learning time (Hrs) 60 04 02 04 04 - - - - - -
Lecture Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Revision Assessment	Contact hours 30	Student learning time (Hrs) 60 04 02 04 04 - - - - - -
Lecture Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Revision Assessment TOTAL	Contact hours 30	Student learning time (Hrs) 60 04 02 04 04 - - - - - -



Theory Assignments					End semester examination		
Lab Assignment & Viva					Viva		
Mapping of assessment with Cos							
Nature of assessment		CO 1	CO 2	CO 3	CO 4		
Sessional Examinatio	n 1	*	*				
Sessional Examinatio	n 2		*	*			
Assignment/Presentat	ion				*		
End Semester Examir	nation	*	*	*	*		
Laboratory examinati	on	*	*	*	*		
Feedback Process	• N	lid-Seme	ster feed	back			
	• E	nd-Semes	ster Feed	lback			
Reference Material	1. Big I	Data: Prin	ciples a	nd best pr	actices of scalable real-	time data	
	syste	ms - Nath	ıan Marz	and Jame	es Warren. Manning Pub	lisher.	
	2. Hado	op: The	Definitiv	ve Guide:	Storage and Analysis a	t Internet	
	Scale	-Tom V	Vhite, O	Reilly Pu	blication 4 th Edition.		
	3. Spark	: The De	finitive	Guide: Bi	g Data Processing Made	Simple –	
	Bill (Chambers	, Matei Z	Zaharia, O	'Reilly Publication 1st E	dition.	
	_			<u>cs/druid.p</u>			
					design.html		
				-	s - IBM developer Work		
				_	orks/library/bd-archpatt		
	6. Big	Data		Analytics	-IBM developer	Works.	
	_	http://www.ibm.com/developerworks/analytics/					
		7. http://lambda-architecture.net/					
	_						
	_	_		_		_	
	10. Mapl	keauce III	orary - h	ttps://githi	ıb.com/twitter/summing	;D1ra	

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



No of Credits:	Prerequisites: Programming in Python, Java										
Synopsis:	This C	ourse p	rovides	insig	ht	on con	cept of b	oig data	characte	eristics, b	atch and
	lambda	archit	ecture;	basic	c f	ile sys	tems in	Big Da	ıta; con	cepts of	Hadoop
	framew	ork, Sp	oark fra	mew	orl	k and th	neir inte	rnals; M	lap-redu	ce progra	amming,
	Spark programming; different layers with use cases demonstrations.										
Course											
Outcomes	On suc	cessful	comple	tion (of	this cou	ırse, stuc	dents wil	ll be abl	e to	
(COs):											
CO 1:	Install	and dev	elop ap	plica	tio	ns usin	g Hadoo	p and it	s ecosys	tems.	
CO 2:	Build a	pplicati	ions usi	ng Sp	par	k frame	ework.				
CO 3:	Build N	Machine	e Learni	ng m	od	lels usir	ng Spark				
Mapping of O	COs to l	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 *	*	*		*		*			*	*	
'	•							1	•	1	•
Course conte	ent and	outcom	es:								
Content					C	ompete	ncies				
Unit 1: Hado	op Ecos	system									
Installation a	and con	figurin	g Hado	oop	1.	Practic	e applic	ations in	HDFS	and YAR	N. (C3)
ecosystem					2. Practice applications using Sqoop, Hive, PI					ve, PIG.	
						(C3)					
					3.	Compu	ite progi	rams usi	ng Map	Reduce. (C3)
Unit 2: Sparl	k Frame	ework		I							
Spark tool ch	nain – I	RDD, I	DataFrai	me,	1.	Develo	p appli	cations	using S	Spark Da	taFrame
SQL and Stre	aming					and S	QL (C4)).			
					2.	Design	real	time ap	plicatio	ns using	g Spark
						Stream	ming (C	4).			
Unit 3: Machine Learning using Spark											



MLIB		1. Compute machine learning models using Spark.			
	(C3)				
Learning strategies, contact h	ours and	student learning	g time		
Learning strategy	Learning strategy		7	Student learning	
				time (Hrs)	
Lecture		12		-	
Seminar		-		-	
Quiz		-		-	
Small Group Discussion (SGD)	1	-		-	
Self-directed learning (SDL)		-		-	
Problem Based Learning (PBL)	j	-		-	
Case Based Learning (CBL)		03		-	
Clinic		-		-	
Practical		24		-	
Revision		03		-	
Assessment		06		-	
TOTAL		48		-	
Assessment Methods:					
Formative:			Summat	tive:	
Internal practical Test			Sessiona	l examination	
Theory Assignments			End sem	ester examination	
Lab Assignment & Viva			Viva		
Mapping of assessment with (Cos				
Nature of assessment	CO 1	CO 2	(CO 3	
Sessional Examination 1	*				
Sessional Examination 2		*	:	*	
Assignment/Presentation	*		*		
End Semester Examination	*	*	:	*	



Laboratory Examinati	on		*	*	*	
Feedback Process	•	Mid-Semester feedback				
	•	En	End-Semester Feedback			
Reference Material	1	. Big	Big Data: Principles and best practices of scalable real-time			
		dat	a systems -	- Nathan Marz and J	ames Warren. Manning	
		Pul	Publisher.			
	2	. Ha	Hadoop: The Definitive Guide: Storage and Analysis at			
		Inte	ernet Scale -	- Tom White, O'Reilly	Publication 4th Edition.	
	3	. Spa	ark: The D	efinitive Guide: Big	Data Processing Made	
		Sin	nple – Bill (Chambers, Matei Zahar	ria, O'Reilly Publication	
		1st	Edition.			

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



Synop	sis:	Students are expected to select a problem in the area of their interest and the									
		area of their specialization that would require an implementation in hardware /									
		software or both in a semester									
Course	e										
Outco	mes	On suc	On successful completion of this course, students will be able to								
(COs)	:										
CO	\ 1	Apply	the obj	ectives	of the	e project	work and	d provide	an ade	quate bac	kground
CO	, 1	with a	detaile	d litera	ture si	urvey					
CO	. 2	Breako	lown th	e proje	ct into	sub bloo	ks with	sufficien	details	to allow	the work
CO	<i>L</i>	to be re	eproduc	ced by	an ind	lependen	research	ner			
CO	. 2	Compo	ose hard	dware/s	softwa	re design	, algorit	hms, flov	vchart, 1	methodol	ogy, and
CO	, 3	block o	diagran	ı							
CO	4	Evalua	ite the r	esults							
CO	5	Summ	arize th	e work	carrie	ed out					
Mappi	ing of (COs to	POs								
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1				*							
CO 2					*			*			
CO 3							*			*	
CO 4						*					*
CO 5							*				
Course	e conte	ent and	outcon	nes:							
Conte	ıt					Compet	encies				
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. Iden	tify the p	oroblem/s	specific	ation (C1)
evalua	tion.					2. Disc	uss the p	oroject (C	22)		
3						3. Prepare the outline (C3)					
						4. Describe the status of the project (C2)					
						5. Prep	are a mi	d-term p	roject p	resentatio	on report
		(C3)									



	6 Duonana and	ant mid town
	6. Prepare and pres	1 0
	presentation slides (C	
	7. Develop project	implementation in
	hardware/software o	r both in chosen platform
	(C5)	
Phase 2		
Status submission, final evaluation.	1. Prepare the progress	report (C3)
	2. Prepare the final pr	roject presentation report
	(C3)	
	3. Prepare and present	final project presentation
	slides (C3, C5)	
	4. Modify and Deve	elop implementation in
	hardware/software o	r both in chosen platform
	(C3, C5)	•
	5. Justify the methods	used and obtained results
	(C6)	
	` ′	
Learning strategies, contact hours an	d student learning time	
Learning strategies, contact hours an		Student learning
Learning strategies, contact hours an Learning strategy	Contact hours	Student learning
Learning strategy		Student learning time (Hrs)
Learning strategy Lecture	Contact hours	
Learning strategy Lecture Seminar	Contact hours	
Learning strategy Lecture Seminar Quiz		
Lecture Seminar Quiz Small Group Discussion (SGD)	Contact hours	
Lecture Seminar Quiz Small Group Discussion (SGD) Self-directed learning (SDL)	48	
Lecture Seminar Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL)		
Lecture Seminar Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL)	48	
Lecture Seminar Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Clinic	48	
Lecture Seminar Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Clinic Practical	48	
Lecture Seminar Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Clinic	48	time (Hrs)
Lecture Seminar Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Clinic Practical		time (Hrs)
Lecture Seminar Quiz Small Group Discussion (SGD) Self-directed learning (SDL) Problem Based Learning (PBL) Case Based Learning (CBL) Clinic Practical Revision	48	time (Hrs)



Assessment Methods:					
Formative:	Summative:				
Project Problem Selectio	Mid-Term	Presentation			
Synopsys review				Second st	atus review
First status review				Demo & I	Final Presentation
Mapping of assessment	with Cos			I	
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5
Mid Presentation	*	*			
Presentation	*	*	*	*	*
Feedback Process	End-Semes	ster Feedl	back		
Reference Material Pa	Particular to the chosen project				

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



~												
Synop	sis:		ŕ				nical lite					
		2. To	Identif	y a cur	rent and	l releva	nt resear	ch topic.	,			
		3. To	prepare	e a topi	c and d	eliver a	presenta	ation.				
		4. To	develo	p the sl	kill to a	uthor a	technica	l report.				
		5. De	velop a	bility to	o work	in grou	ps to rev	iew and	modi	fy t	echnical	content.
Course	e											
Outco	mes	On suc	cessful	compl	etion of	f this co	urse, stu	dents wi	ll be	abl	e to	
(COs)	:											
CO 1			compet under d			ying rel	evant in	formatio	n, de	finiı	ng and ex	plaining
CO 2			-		workin ormatio	_	a method	lology, s	truct	urin	g their o	al work,
CO 3		_		_			bulary, a and pac		demo	onst	rate com	mand of
CO 4			nstrate d const		-	paid c	lose atte	ention to	wha	t ot	hers say	and can
CO 5		structu depth synthe	red, and of kno	d logica owledg	al seque	ence, re omplex	spond re	spectfull ts, and	y to o	oppe	osing ide	g, well- as, show bility to
Mappi	ing of	COs to	POs									
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO	0	PO 10	PO 11
CO 1	*	FO 2	103	FU 4	103	100	107	*	*	9	FO 10	*
CO 2	*							*	*			*
CO 3	*							*	*			*
CO 4	*							*	*			*
CO 4	*							*	*			*
		otorias.	aorta -	t ba	g ord =	tudant	laaw					·
			contac	ı nour	s and s		learning	g ume		G.		1
Learnii	ng stra	tegy				Conta	ct hours				udent ne (Hrs)	learning
Lecture	e	·				-				-		



Seminar			-			-
Quiz			-			-
Small Group Discussi	ion (SGD)		14			-
Self-directed learning	(SDL)		-			-
Problem Based Learn	ing (PBL)		-			-
Case Based Learning	(CBL)		-			-
Clinic			-			-
Practical			-			-
Revision			-			-
Assessment			-			-
TOTAL			14			-
Assessment Methods	S:	<u>'</u>				
					Summat	tive:
Formative:						
Formative: Seminar Topic Select	ion					
	ion					
Seminar Topic Select	ion					
Seminar Topic Select	ion					
Seminar Topic Select		S				
Seminar Topic Select Synopsys review PPT Review		s	CO 2	CO 3	CO 4	CO 5
Seminar Topic Select Synopsys review PPT Review Mapping of assessment			CO 2	CO 3 *		CO 5
Seminar Topic Select Synopsys review PPT Review Mapping of assessment Nature of assessment	ent with Co	CO 1	*	*	CO 4	

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



Synop	sis:	This c	ourse in	ntroduc	es adva	anced a	pplicati	ons of pi	robability	and stat	istics for
		multiv	ariate a	nd time	e series	data.					
Course	e										
Outco	mes	On suc	ccessful	compl	etion o	f this co	ourse, st	udents w	ill be ab	le to	
(COs)	•										
CO	1:	Compu	ite and i	nterpret	descrip	tive stati	stics for	multivar	iate data		
CO	2:	Apply perform		nd logis	tic regre	ession m	odels fo	or practica	ıl problem	ns and asse	ess model
CO	3:	_	et the ou nension 1		_	l compo	nent ana	lysis (PCA	A) applied	to multiva	riate data
CO	4:	1	y multiv		data w	ith mix	ed data	type fea	atures and	d cluster	using an
CO	5:	Unders	stand the	basics	of time	series m	odelling	and appl	y to real-l	ife problei	ns
Mappi	ing 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	*	*	*								
Cours	e conto	ent and	outcon	ies:			1	1	1		
Conte	1t					Compet	oncios				

Competencies
 Understand the organisation of multivariate data (C2). Relate multivariate population and sample parameters (C4). Understand and apply multivariate Gaussian modelling to practical problems (C2, C3). Compare parameter estimation using different probabilistic approaches (C4).



Unit 2: Linear and Logistic Regression

Simple linear regression – regression model, estimating and interpreting coefficients, accuracy of coefficient estimates and model, ANOVA, R2 statistic - Multiple linear regression coefficients, estimating qualitative predictors, interaction effects, potential problems - Logistic regression - binary and multinomial logistic regression models, estimating and interpreting coefficients. assessing model calibration and discrimination, area under the ROC curve.

- 1. Model a linear relationship between input and output variables and assess model performance (C5).
- 2. Use different performance metrics to conclude what is a good linear fit to the data (C6).
- 3. Interpret model coefficients and investigate the effect of input variables on output through sensitivity analysis (C6).
- 4. Apply logistic regression modelling for binary and multiclass classification and assess model performance (C6).

Unit 3: Principal Component Analysis; Cluster Analysis

Geometric intuition of principal components - Maximum variance perspective - algebraic setup, eigenvectors and eigenvalues of sample correlation matrix - Interpretation and application of principal components for dimension reduction.

Dissimilarity measures for mixed data types - Partition around medoids (PAM) vs. K-means algorithms - Selecting the number of clusters.

- 1. Understand the mathematical foundation of principal component analysis (PCA) (C2).
- 2. Perform and interpret the output of PCA applied to multivariate data for dimension reduction (C6).
- 3. Assess when PCA is applicable for clustering multivariate data (C6).
- 4. Compare and contrast methods for clustering multivariate data with mixed data types (C6).

Unit 4: Bootstrapping; Time Series Analysis



Time series concepts: stationarity, trend, seasonality, autocorrelation - Autoregressive moving average (ARMA) models - Resampling, smoothing, windowing, and rolling average - First and second order differencing - Validating time series predictions.

- 1. Understand the basic principles of bootstrapping as an experimental method to estimate the sampling distributions of a statistic (C2).
- 2. Understand the basic mathematical principles of time series modelling (C2).
- 3. Apply time series modelling to practical problems (C3).
- 4. Interpret the results of times series model predictions (C3).

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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	e:
Internal practical Test				Sessional e	xamination
Theory Assignments				End semest	er 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/Presentat	ion	*	*	*	*	*
End Semester Examir	nation	*	*	*	*	*
Feedback Process			ster feedb			
	• End	ı-Semes	ster Feedl	раск		
Reference Material	1. An Intr	oductio	n to Sta	tistical Le	arning with App	olications in R,
	Gareth Jan	nes, Dai	niela Wit	tten, Trevo	or Hastie and Ro	bert Tibshirani,
	Springer; 1	st Editi	on, 2013,	, Corr. 7th	printing 2017 Ed	lition.
	2. An Intr	oductio	n to App	olied Mult	ivariate Analysis	with R, Brian
	Everitt and	Torster	n Hothori	n– Springe	r Publications,1s	t Edition, 2011.
	3. Machin	e Learn	ing - A P	robabilisti	c Perspective, Ke	evin P. Murphy,
	The MIT P	ress; 1s	t Edition	, 2012.		
	4. Mathem	natics fo	r Machin	e Learning	g, Marc Peter Dei	senroth, A Aldo
	Faisal, and	Cheng	Soon O	ng, Camb	ridge University	Press, 2020. –
	Online res	source	from Ca	ambridge	University Pres	ss available at
	https://mm	l-book.g	github.io/	/book/mml	-book.pdf	

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



Acaden	nic Yea	r:2020-2	2021		Sem	est	ter:First	Year, S	Semester 2	2		
No of C	redits:	1			Prei	req	uisites:	MCL 60)2			
Synops	sis:	This co	ourse in	troduce	s adv	van	ced ap	plicatio	ns of pro	obability	and stat	istics for
		analysi	ng mult	tivariate	e and	tin	ne serie	s data u	sing the	R progra	amming la	anguage.
Course)											
Outcor	nes	On suc	cessful	comple	etion (of 1	this cou	rse, stu	dents wi	ll be abl	e to	
(COs):												
CO 1:		Compu	ite and i	interpre	t des	crij	ptive sta	atistics	for multi	ivariate (data	
CO 2:		Build a	nd asse	ss linea	ır and	l lo	gistic r	egressio	on mode	ls for pra	actical pro	oblems
CO 3:		Perform multiva	_	_	ompo	nei	nt anal	ysis (P	CA) for	dimens	sion redu	iction in
CO 4:		Cluster	multiv	ariate d	ata w	ith	n mixed	data ty	pes			
CO 5:		Apply	time sei	ries mo	dellin	ıg t	to real-l	ife prol	olems			
Mappi	ng of (COs to 1	POs									
COs	PO 1	PO 2	PO 3	PO 4	PO.	5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1	*	*	*		*							
CO 2		*	*	*	*				*			
CO 3		*	*	*	*				*			
CO 4		*	*	*	*		*		*			
CO 5	*	*	*									
Course	conte	nt and	outcom	es:					•		1	
Conten	et e					Co	ompeter	ncies				
Unit 1:	Multi	variate	Distrib	outions								
Mean v	ector,	covariar	ice and	correlat	ion	1.	Comp	oute de	scriptive	statistic	es of mu	ltivariate
- pop	oulation	n vs.	sample	e - 7	Гће		data (C2).				
multiva	riate	Gauss	ian -	– joi	nt-,	2.	Perfo	rm e	xplorato	ry dat	a analy	ysis of
margin	al-, and	d conditi	onal dis	stributio	ons,		multi	variate	data (C4).		
Mahala	nobis	distanc	e and	outlier	s -	3.	Identi	fy outli	ers in m	ultivaria	te data (C	C3).
Propert	ies of	the mul	tivariate	e Gauss	sian	4.	Visua	lise ar	nd unde	rstand t	he prope	erties of
- Para	ameter	estima	ation:	maxim	um		multi	variate	Gaussiar	n data (C	23).	
likeliho	od e	estimatio	on (M	(LE)	and							



maximum	aposteriori	estimation
(MAP).		

Unit 2: Linear and Logistic Regression

Simple linear regression – regression model, estimating and interpreting coefficients, accuracy of coefficient estimates and model, ANOVA, R2 statistic - Multiple linear regression estimating coefficients, qualitative predictors, interaction effects, potential problems - Logistic regression – binary and multinomial logistic regression models, estimating and interpreting coefficients. assessing model calibration and discrimination, area under the ROC curve.

- 1. Use in-built functions in R to build linear models for practical problem (C3).
- 2. Compute different performance metrics to assess model performance (C6).
- 3. Interpret model coefficients and investigate the effect of input variables on output through sensitivity analysis (C6).
- 4. Use in-built functions in R to build logistic regression models for practical binary classification problems and assess model performance (C6).

Unit 3: Principal Component Analysis; Cluster Analysis

Geometric intuition of principal components - Maximum variance perspective - algebraic setup, eigenvectors and eigenvalues of sample correlation matrix - Interpretation and application of principal components for dimension reduction.

Dissimilarity measures for mixed data types - Partition around medoids (PAM) vs. K-means algorithms - Selecting the number of clusters.

- 1. Visualise the geometric interpretation of principal component analysis (PCA) (C3).
- 2. Use in-built functions in R to perform PCA on multivariate data (C3).
- 3. Compare and contrast PCA for variance maximization vs. clustering of multivariate data (C6).
- 4. Cluster multivariate data with mixed data types using in-built functions in R (C3).

Unit 4: Bootstrapping; Time Series Analysis

Time series concepts: stationarity, trend, seasonality, autocorrelation -Autoregressive moving average 1. Apply bootstrapping on a practical data set and assess performance (C3).



	(ARMA)	mode	ls -	Resa	mpling,
	smoothing,	wind	owing	g, and	rolling
	average -	First	and	second	order
	differencing	g - Va	alidati	ng time	series
	predictions.				
ı					

- 2. Understand and apply in-built functions in R for time series modelling (C3).
- 3. Apply time series modelling to practical problems (C3).
- 4. Interpret the results of times series model predictions (C3).

Learning strategies, contact hours and student learning time Learning strategy Contact hours

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:

Sessional Examination 1

Formative:	Summative:							
Internal practical Test	Sessional examination							
Theory Assignments	End semester examination							
Lab Assignment & Viva	Viva							
Manning of aggaggment wit	h Coa							
Mapping of assessment with Cos								
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5			



Sessional Examinatio	n 2			*	*	*			
Assignment/Presentat	ion	*	*	*	*	*			
Laboratory examinati	on	*	*	*	*	*			
Feedback Process	• Mic	d-Semes	ster feedb	ack		1			
	• End	d-Semes	ster Feedl	oack					
Reference Material	1. An Intr	oductio	n to Sta	tistical Le	arning with App	plications in R,			
	Gareth Jan	nes, Da	niela Wit	ten, Trevo	or Hastie and Ro	bert Tibshirani,			
	Springer; 1st Edition, 2013, Corr. 7th printing 2017 Edition.								
	2. An Intr	oductio	n to App	olied Mult	ivariate Analysis	s with R, Brian			
	Everitt and	Torste	n Hothori	n– Springe	r Publications,1s	et Edition, 2011.			
	3. Machin	e Learn	ing - A P	robabilisti	c Perspective, Ko	evin P. Murphy,			
	The MIT P	ress; 1s	t Edition,	, 2012.					
	4. Mathem	natics fo	r Machin	e Learning	g, Marc Peter Dei	senroth, A Aldo			
	Faisal, and Cheng Soon Ong, Cambridge University Press, 2020								
	Online resource from Cambridge University Press available								
	https://mm	l-book.ş	github.io/	/book/mml	-book.pdf				

Name of the Program:	ME in Machine Learning
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Course	Title:				Ma	chine Learning Principles & Applications						
Course	Code:	MCL 60	4		_	urse Instructor:						
Acaden	nic Yea	r: 2020-	2021		Sen	emester:First Year, Semester 2						
No of Credits: 3							iisites	:MCL 6	601, 603, 6	05		
Synops	sis:	This co	ourse p	rovides	s an a	adva	nced	treatme	ent of ma	chine le	arning al	gorithms
		and the	under	lying n	nathei	matio	cs ess	sential f	or carefu	l selectio	on and an	alysis of
		algoritl	hms for	practi	cal ap	plica	ations	S.				
Course	e											
Outco	mes	On suc	cessful	compl	etion	of th	nis co	urse, st	udents wi	ll be abl	e to	
(COs):												
CO	1:	Develo	p practio	cal expe	rience	with	ı state	-of-the-	art machin	e learning	g tools and	libraries.
СО	2:	Differen machine			disc	rimir	native	and g	enerative	algorith	ms for si	upervised
СО	3:	Evaluat	e machi	ine leari	ning a	lgori	thms	for accu	racy and p	erforman	ice.	
СО	4:		_			-	th pra	ctical di	fficulties i	n applyin	g machine	elearning
		techniq					1 0	- 11				
СО	5:	Develop features	_	ımensi	onal 1	mode	els of	applica	tion prob	lems wit	h mixed	data type
Manni	ng of (COs to 1										
											1	
COs	PO 1	PO 2	PO 3	PO 4	PO 5	P	PO 6	PO 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	ıt					Co	mpet	encies				
Unit 1	Kern	el Meth	ods; L	inear I	Regre	ssio	n					
Kernel	s as	feature	maps	- Ke	ernel	1.	Und	erstand	the rela	tionship	between	n kernel
functio	ns: ty	pes, h	yperpai	rametei	rs -		func	tions ar	nd feature	mappin	g (C2).	
Kernel matrix: interpretation and						2. Understand how to develop nonlinear models						
propert	roperties - Kernel (nonlinear) SVM. from linear ones using kernels (C2, C5).).				
3.						3.	3. Construct the cost function for least mean					
Least mean squares (LMS) algorithm:						squares algorithm and apply gradient descent						
cost	functio	n - (Gradier	nt des	cent		(C5)					
algorith	nm: le	earning	rate,	batch	and							



stochastic gradient approaches -Probabilistic interpretation of linear regression: MLE and MAP estimates. 4. Compare probabilistic interpretation of linear regression with linear algebra-based interpretation (C6).

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

Gaussian discriminant analysis (GDA) -Naive Bayes algorithm: MLE estimates, Laplace smoothing.

Grid search for best hyperparameters Cross validation: types and practical
approaches - Featureselection:
forward/backward search, wrapper
model & filter feature selection Metrics for evaluating supervised &
unsupervised machine learning
algorithms.

- 1. Model data flexibly by specifying a proper probabilistic model (C4).
- 2. Develop an optimization view of machine learning through MLE estimates (C5).
- 3. Understand how to efficiently identifyoptimal values of hyperparameters using grid search (C2, C3).
- 4. Choose appropriate feature engineering approaches and quantitatively compare machine learning algorithms (C6).

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

Modifying the training data: over- and under-sampling - Modifying the loss function.

Clustering with a mixture of Gaussians

- Expectation maximization (EM) framework.

Factor analysis (FA) - Generalized low rank models (GLRM).

Independent Component Analysis (ICA)

- 1. Compare different approaches for dealing with missing data (C6).
- 2. Relate the EM framework for clustering with K-means clustering.
- 3. Construct and interpret low dimensional models of data (C5).
- 4. Develop models for analysingmixed datatype data (C5).



Learning strategies, conta	act hou	rs and	student	learning	time			
Learning strategy			Conta	ect hours		Student learning		
				time (Hrs)				
Lecture			30			60		
Quiz			02			04		
Small Group Discussion (S	GD)		02			02		
Self-directed learning (SDI	L)		-			04		
Problem Based Learning (I	PBL)		02			04		
Case Based Learning (CBI	٦)		-			-		
Revision			02			-		
Assessment			06			-		
TOTAL			44			74		
Assessment Methods:								
Formative:					Summative:			
Internal practical Test					Sessional	examination		
Theory Assignments				End semester examination				
Lab Assignment & Viva				Viva				
Mapping of assessment w	rith 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	<u> </u>	*	*	*	*	*		
Feedback Process	Mic	l Samai	ster feed	back				
•	Enc	ı-Semes	ster Feed	васк				
Reference Material 1. A	A Cours	se in M	Sachine 1	Learning,	Hal Daumé	III – Online resource		
	available at http://ciml.info/							
2. 1	Machine	Learni	ng: A P	robabilistic	Perspective.	, Kevin Murphy, MIT		
	Press,20	17.						



- 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
- 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/mmlbook.pdf
- 6. Pattern Recognition and Machine Learning, Christopher Bishop, Springer Publications, 2017.

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



Acader	Academic Year: 2020-2021 Semester: First Year, Semester 2												
No of Credits: 1 Pre					Prere	Prerequisites: MCL 604							
Synop	sis:	This course provides a practical introduction to advanced machine learning algorithms with an emphasis on careful analysis and selection of algorithms for practical problems.											
Course	e												
Outco	mes	On suc	cessful	compl	etion o	f this co	urse, 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	ibraries.			
CO 2:		-			-	iscrimin		nd gener	ative su	pervised	machine		
CO 3:		Evalua practic			earning	g algori	thms fo	or accura	acy and	perform	ance for		
CO 4:		Implen data.	nent di	fferent	strategi	ies for s	electing	g features	and dea	ling with	missing		
CO 5:		Implen feature		achine	learnir	ng mode	els for	real-life	data witl	h mixed	datatype		
Mappi	ng of	COs to 1	POs										
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11		
CO 1			*		*								
CO 2		*	*	*	*								
CO 3		*	*	*	*			*					
CO 4		*	*	*	*								
CO 5		*	*	*	*	*				*			
Course	e conte	ent and	outcon	ies:									
Conten	ıt					Compet	encies						
Unit 1	: Kern	el Meth	ods; L	inear I	Regress	sion							
Kernel	s as	feature	maps	- Ke	ernel	l. Imp	lement	and com	pare diff	ferent ke	rnels for		
functio	ns: ty	pes, h	yperpai	rametei	·s -	featı	ıre map	ping (C4).				
Kernel	mat	rix: in	terpreta	ation	and 2	2. Imp	lement	kernel S	SVM and	d investi	gate the		
propert	ties - K	ternel (n	onlinea	ır) SVN	1.	effec	cts of		el para	meters	through		
						, 10 u	ZutiU	(- 1).					



Least mean squares (LMS) algorithm:
cost function - Gradient descent
algorithm: learning rate, batch and
stochastic gradient approaches Probabilistic interpretation of linear
regression: MLE and MAP estimates.

- 3. Implement gradient descent for least mean squares algorithm and investigate the effects of hyperparameters on performance (C4).
- 4. Compare linear regression applied to practical problems with and without regularization (C4).

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

Gaussian discriminant analysis (GDA) -Naive Bayes algorithm: MLE estimates, Laplace smoothing.

Grid search for best hyperparameters Cross validation: types and practical
approaches - Featureselection:
forward/backward search, wrapper
model & filter feature selection Metrics for evaluating supervised &
unsupervised machine learning
algorithms.

- 1. Implement probabilistic models of data (C4).
- 2. Perform grid search to identify best model hyperparameters (C3).
- 3. Perform feature engineering for real-life problems (C3).
- 4. Evaluate machine learning algorithms using well established performance metrics (C3).

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

Modifying the training data: over- and under-sampling - Modifying the loss function.

Clustering with a mixture of Gaussians
- Expectation maximization
(EM)framework.

Factor analysis (FA) - Generalized low rank models (GLRM).

- 1. Implement and compare different approaches for dealing with missing data in real-life problems (C6).
- 2. Implement and interpret low dimensional models of data (C4).
- 3. Implement models for analysing mixed datatype data (C4).



Independent Component Analysis	s 4. Co	ompare and	contrast dif	ferent techniques for			
(ICA)	di	dimension reduction and their practical					
	in	plications ((C6).				
Learning strategies, contact hours ar	nd studer	nt learning	time				
Learning strategy	Con	tact 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:			Summati	ve:			
Internal practical Test			Sessional	al examination			
Theory Assignments			End seme	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 *	*	*	*	*			
Laboratory examination *	*	*	*	*			



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

Name of the Program:	ME in Machine Learning
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Course	Title:				Deep	Deep Learning							
Course	Code:	MCL 60	6		Cour	Course Instructor:							
Acade	nic Yea	c Year: 2020-2021				Semester:First Year, Semester 2							
No of (Credits	: 3			Prere	equisites	:MCL 6	501, 603, 6	505				
Synop	sis:	This co	-			_	nputatio	onal foun	dation to	the prin	ciples of		
Outco	Course Outcomes On successful completion of this course, students will be able to (COs):												
CO	1:	Gain a	solid un	derstan	ding of t	ing of the mathematical basis of neural networks.							
CO	2:	Develo	p praction	cal expe	rience with state-of-the-art deep learning tools and libraries.								
CO	3:	Build a	nd analy	se deep	learnin	learning models for application problems.							
CO	4:	Devise	techniq	ues for i	mprovi	proving the way neural networks learn.							
CO	5:	Develo	p skills	to choos	se an ap	propriate	e deep le	earning mo	odel.				
Mapp	ng of	COs to 1	POs										
COs	PO 1	PO 2 PO 3 PO 4 PO 5 PO 6 PO 7 PO 8 PO 9 PO 10 PO 11								PO 11			
CO 1	*	*											
CO 2	*	*	*		*								
CO 3		*	* * * *										

Course content and outcomes:

CO 4

CO 5

Content	Competencies

Unit 1: Introduction to Deep Learning; Matrix Calculus; Logistic Regression

neural networks.

Derivatives in one dimension Derivative in multiple dimensions:
gradient and Jacobian matrices - Rules
of matrix calculus: product and chain
rules -Optimizing using the gradient
descent method—intuition and principle.

Sigmoid neurons - The architecture of

- 5. Understand the basic architecture of a sigmoid neuron (C2).
- 6. Reconstruct derivatives of multivariable functions using ideas from single variable calculus and linear algebra (C5).
- 7. Develop intuition behind the gradient descent method (C5).
- 8. Formulate the cost function for binary classification using logistic regression using vectorized approach (C5).



Binary	cla	ssificat	ion	using	logistic		
regressio	on:	cost	fun	ction,	gradient		
descent, and vectorization.							

Unit 2:Shallow Neural Network

One hidden layer neural network: architecture and notation - The role of activation functions and their derivatives - Forward propagation using matrix-based approach - Cost/loss function: intuition and setup - Gradient descent: backpropagation intuition and vectorized setup using matrix-based approach - Random initialization of network parameters.

- 5. Develop intuition for nonlinear activation functions (C5).
- 6. Formulate backpropagation using matrix-based approach (C5).
- 7. Develop intuition for and formulate loss functions in deep learning (C5).
- 8. Understand the importance of random initialization of network parameters (C2).

Unit 3:Deep Neural Network; Improving the Way neural Networks Learn

Deep L-layer neural network: architecture, notation, and building blocks - Forward and backward propagation in a deep neural network using matrix-based approach - The importance of deep representations - Parameters vs. hyperparameters.

The cross-entropy cost function - The learning slowdown problem - Overfitting and regularization: L1/L2, dropout - Weight initialization.

- 1. Extend ideas from shallow neural network to a deep neural network (C2).
- 2. Formulate forward and backward propagation for a deep neural network using matrix-based approach (C5).
- 3. Compare and contrast parameters and hyperparameters (C6).
- 4. Gain an intuitive understanding of overfitting and the use of regularization using different approaches (C2).

Unit 4: Hyperparameter Tuning; Recurrent Neural Networks

Random initialization using appropriate scales - Batch normalization.

- 5. Understand how to tune hyperparameters (C2).
- 6. Intuitively understand the architecture of a recurrent neural network (C2).



Recurrent neural network: architecture							
and notation - Forward and backward							
propagation through time - Different							
types of recurrent neural networks and							
their applications.							

Feedback Process

- 7. Compare and contrast feed forward and recurrent neural networks (C6).
- 8. Understand how to perform forward and backward propagation for recurrent neural networks.

Learning strategies, contact l	nours and	student	learning	time				
Learning strategy		Conto	act hours		Student learning			
_					time (F	1rs)		
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	44			74		
Assessment Methods:								
Formative:				Summati	ve:			
Internal practical Test				Sessional	al examination			
Theory Assignments				ster exa	mination			
Lab Assignment & Viva				Viva	Viva			
Mapping of assessment with	Cos							
Nature of assessment	CO 1	CO 2	CO 3	CO 4	C	O 5		
Sessional Examination 1	*							
Sessional Examination 2	*	*	*					
Assignment/Presentation	*	*	*	*				
End Semester Examination	*	*	*	*	*			

Mid-Semester feedback



	•	End	-Semester I	Feedb	oack				
Reference Material	7.	Neural N	letworks and	d Deep	p Learning, Michae	el Nielsen – Deteri	mination		
		Press	_		Available	online	at		
		http://neuralnetworksanddeeplearning.com/index.html							
	8.	Lecture	slides of Pro	of. An	ndrew Ng – Stanfo	ord University – A	vailable		
		online a	https://cs23	0.stan	ford.edu/syllabus/				
	9.	Deep Le	arning, Ian C	Goodfe	ellow, Yoshua Ben	gio, and Aaron Co	urville –		
		MIT Pre	ss – Availab	le onl	ine at http://www.c	leeplearningbook.o	org/		

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



Course Code:MCL 606L Cou						ourse Instructor:						
Academic Year: 2020-2021 Sen						ster:Firs	st Year,	Semester 2	2			
No of Cred	No of Credits: 1 Prerequisites: MCL 606											
Synopsis:	This c	This course provides a practical foundation to implementing deep learning										
	algorit	algorithms for real-life problems using state of the art software.										
Course												
Outcomes	On suc	ccessful	compl	etion	of	this co	urse, st	udents wi	ll be abl	e to		
(COs):												
CO 1:	Gain a	deeper ı	understa	nding	g of	f matrix	calculus	s through I	ython pr	ogrammir	ng.	
CO 2:								art deep le		ols and li	braries.	
CO 3:	Implen	nent dee	p learni	ng mo	ode	els for ap	plicatio	n problem	S.			
CO 4:								eural netw				
CO 5:	Numer	ically ar	nalyse do	eep le	arn	ning moo	dels and	select the	best mod	lel.		
Mapping of	of COs to	POs										
COs PO	1 PO 2	PO 3	PO 4	PO.	5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	
CO 1 *				*								
CO 2	*	*		*								
CO 3	*	*	*	*								
CO 4	*	*	*	*								
CO 5	*	*	*	*		*		*				
Course con	ntent and	outcon	nes:									
Content					Competencies							
Unit 1: Int	roduction	to Dec	ep Leai	ning	;; N	Matrix	Calcul	us; Logis	tic Regr	ession		
Sigmoid no	eurons - 7	The arcl	hitectur	e of	1	. Impl	ement a	a sigmoid	neuron i	from scra	tch (C3).	
neural netv		ino uro		• 01	2	. Impl	ement	forward a	nd back	ward pro	pagation	
Derivatives		ne dir	nensior	1 -		for a	sigmoi	id neuron	(C3).			
Derivative	in mul	tiple o	limensi	ons:	3. Implement gradient descent for a sigmoid							
gradient ar	d Jacobia	n matri	ces - R	ules		neur	on (C3)).				
of matrix	calculus:	product	and c	hain	4	. Impl	ement	cost	function	n for	binary	
of matrix calculus: product and chain rules -Optimizing using the gradient						classification using logistic regression using						
descent me		•				vecto	orized a	approach ((C3).			
			_	-								



Binary cl	assifica	tion using	g logistic					
regression:	cost	function,	gradient					
descent, and vectorization.								

Unit 2:Shallow Neural Network

One hidden layer neural network: architecture and notation - The role of activation functions and their derivatives - Forward propagation using matrix-based approach - Cost/loss function: intuition and setup - Gradient descent: backpropagation intuition and vectorized setup using matrix-based approach - Random initialization of network parameters.

- 1. Visualize different nonlinear activation functions (C3).
- 2. Implement forward and backward propagation for a shallow neural network using matrix-based approach (C3).
- 3. Implement gradient descent method for a shallow neural network (C3).
- 4. Numerically investigate the effect of random initialization of network parameters (C4).

Unit 3:Deep Neural Network; Improving the Way neural Networks Learn

Deep L-layer neural network: architecture, notation, and building blocks - Forward and backward propagation in a deep neural network using matrix-based approach - The importance of deep representations - Parameters vs. hyperparameters.

The cross-entropy cost function - The learning slowdown problem - Overfitting and regularization: L1/L2, dropout - Weight initialization.

- Visualise architecture of a deep neural network (C3).
- 2. Implement forward and backward propagation for a deep neural network using matrix-based approach (C3).
- 3. Implement deep neural networks using in-built libraries for real-life problems (C4).
- 4. Implement different regularization approaches and compare their advantages and disadvantages (C6).

Unit 4: Hyperparameter Tuning; Recurrent Neural Networks

Random initialization using appropriate scales - Batch normalization.

- 1. Fine tune hyperparameters (C3).
- 2. Numerically investigate the effect of random initialization in deep neural networks (C4).



Recurrent neural network: architecture							
and notation - Forward and backward							
propagation through time - Different							
types of recurrent neural networks and							
their applications.							

- 3. Visualise the architecture of a recurrent neural network (C3).
- 4. Implement recurrent neural network models for real-life problems.

their applications.							
Learning strategies, contact	hours and	l studen	t learning	time			
Learning strategy			tact hours	Student learning time (Hrs)			
Lecture		12			-	(1173)	
Seminar		-			-		
Quiz		-			-		
Small Group Discussion (SGI))	-			-		
Self-directed learning (SDL)		-			-		
Problem Based Learning (PBI	L)	-			-		
Case Based Learning (CBL)		03			-		
Clinic		-			-		
Practical		24			-		
Revision		03			-		
Assessment		06		-			
TOTAL		48	48				
Assessment Methods:							
Formative:				Summati	ive:		
Internal practical Test				Sessional	al examination		
Theory Assignments				End seme	ester examination		
Lab Assignment & Viva			Viva				
Manning of aggagement with	Cas						
Mapping of assessment with				T GO 4		T GO 7	
Nature of assessment	CO 1		CO 3	CO 4		CO 5	
Sessional Examination 1	*	*	*	*			
Sessional Examination 2	Sessional Examination 2					*	



Assignment/Presentat		*	*	*	*	*				
Laboratory examinati	on		*	*	*	*	*			
Feedback Process	•	Mic	l-Seme	-Semester feedback						
	•	Enc	l-Seme	ster Fee	edback					
Reference Material	1.	Neural N	Network	ks and D	Deep Learr	ning, Michael	l Nielsen – De	etermination		
		Press		_	Av	ailable	online	at		
		http://ne	uralnet	worksan	ıddeeplear	arning.com/index.html				
	2.	Lecture	slides of Prof. Andrew Ng - Stanford Univ					– Available		
	online at https://cs230.stanford.edu/syllabus/									
	3.	Deep Le	arning,	Ian Goo	odfellow, Yoshua Bengio, and Aaron Courville –			Courville –		
	MIT Press – Available online at http://www.deeplearningbook.org							ok.org/		
	1									

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



Course Code:MCL 608 Cou						Course Instructor:						
Academic Year: 2020-2021 Sem						neste	er:Firs	st Year,	Semester 2	2		
No of C	Credits:	<u> </u>										
Synop	sis:	This co	This course provides a thorough computational foundation to the principles of									
		reinforcement learning and its applications.										
Course	e											
Outco	mes	On successful completion of this course, students will be able to										
(COs):												
СО	1:	non-inte	eractive	machin	e lear	ning			ning that d			
СО	2:						_		nce learnin on to achie			gramming
СО	3:	Decide problen			_				rmulated a	as a rein	forcement	learning
СО	4:								nforcemen	nt learnin	g algorith	ms.
СО	5:	Analyse	e algorit	hms for	reinfo	orcei	ment 1	earning.	•			
Mappi	ng of (COs to l	POs									
COs	PO 1	PO 2	PO 3	PO 4	PO 5	P	06	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1	*											
CO 2	*	*										
CO 3		*	*	*								
CO 4		*	*	*	*							
CO 5		*	*	*	*		*					
Course	e conte	nt and	outcon	nes:								
Conten	ıt					Co	mpete	encies				
Frame	work;	duction Dynam			ing				roblem; 1			
Examp		and learni	elem		of ions	1.	Gain		intuiti ent learni		iderstandi	Ü
		reinfor	•						st it with	_		
	•	nforcem			**************************************							_
						2.	algorithms such as deep learning (C2, C6). 2. Demonstrate the exploration versus					
n-Armed bandit problem: action-value									dilemma	-		
method	ls -]	Finite	Marko	v deci	sion		prob	lem (C	3, C4).			
process	s: tl	he a	gent–e	nvironr	nent							



interface,	goals and	l rewards,	returns,
Markov	decision	processes,	value
functions,	and optim	al value fui	nctions.

- 3. Gain an intuitive understanding of a Markov decision process (C2).
- 4. Formulate a reinforcement learning task as a Markov decision process (C5).

Unit 2:Model Free Reinforcement Learning

Generalized	policy	iterati	on -
Importance of	explorat	ion -	Monte
Carlo control	- Tempo	ral dif	ference
methods for con	ntrol.		

- 1. Understand policy iteration using an iterative policy evaluation approach (C2, C4).
- 2. Understand how policy evaluation and policy improvement processes interact (C2, C4).
- 3. Solve reinforcement learning tasks using Monte Carlo methods (C3, C4).
- 4. Combine dynamic programming and Monte Carlo ideas to formulate temporal difference methods for solving reinforcement learning tasks (C5).

Unit 3:Approximate Solution Methods; Policy Based Methods

Value prediction with function approximation - Gradient-descent methods - Linear methods - Control with function approximation.

Policy gradient - Actor-critic methods -Policy-based vs. value-based methods -Integrating supervised & reinforcement learning.

- 1. Formulate function approximation methods for value prediction (C5).
- 2. Understand the assumptions of linear value function approximators (C2).
- 3. Compare and contrast policy-based and value-based methods for reinforcement learning (C6).
- 4. Explore integration of supervised and reinforcement learning (C5).

Learning 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	exam	nination
Theory Assignments				End seme	ster e	xamination
Lab Assignment & Viva				Viva		
Mapping of assessment with Co	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	*	*	*	*		*
Reference Material 1. Reinford G. Bar https://w k2ndEd 2. Lecture online a 3. Generati and Play 4. Reinford	back Process Mid-Semester f End-Semester f Reinforcement Learn G. Barto, MIT https://web.stanford.ok/2ndEd.pdf Lecture slides of Prof online at http://web.st					able online at onBartoIPRLBoo ersity – Available atml Write, Compose,

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



Course Code:MCL 608L Cou				ourse Instructor:							
Academic Year: 2020-2021 Sem					mester:First Year, Semester 2						
No of C	Credits	: 1			Pre	requisite	s:MCL 6	508			
Synop	sis:		_		_				_	ing reinfo	
		learnin	g algor	ithms f	or rea	ıl-life pro	blems u	ısing stat	e of the a	art softwa	re.
Course	e										
Outco	mes	On suc	cessful	comple	etion	of this co	ourse, st	udents w	ill be abl	e to	
(COs):											
CO 1:						_	loration	vs. explo	itation ap	proaches i	n solving
CO 2:		reinford					o colvo	reinforcen	ant lagrn	ing tooks	
		•								ing tasks.	
CO 3:		Model	real-life	problen	ns usi	ng Marko	v decisio	on process	ses.		
CO 4:		Compa tasks.	re and	contra	ist se	veral me	ethods f	for solvii	ng reinfo	orcement	learning
CO 5:		Compu	tational	ly analy	se alg	orithms fo	or reinfo	rcement le	earning.		
Mappi	ng of (COs to	Pos								
COs	PO 1	PO 2	PO 3	PO 4	PO S	5 PO 6	PO 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	ies:				1			
Conten	ıt					Compet	encies				
Frame	Unit 1: Introduction to the Reinforcement Learning Problem; Reinforcement Learning Framework; Dynamic Programming										
Examp	les	and	elem	ents	of	1. Imp	lement	building	g blocks	s for so	olving a
reinfor	cemen	t learni	ng - 1	Limitat	ions	rein	forceme	ent learni	ng task (C3).	
and sc	ope of	reinfor	cement	learnii	ng -	2. Solv	e an n-A	Armed ba	ndit prob	lem using	different
History	of rei	nforcem	ent lea	rning.		expl	oration s	strategies ((C3).		
3. Implement Markov						decision	process	models			
n-Arm	ed ban	dit prob	olem: a	ction-v	alue	(C3)).				
		-									
	methods - Finite Markov decision										



process:	the	agent-enviro	onment
interface,	goals a	nd rewards, r	eturns,
Markov	decision	processes,	value
functions,	and opti	mal value fund	ctions.

Unit 2:Model Free Reinforcement Learning

Generalized	policy	iterati	on -
Importance of	explorat	ion -	Monte
Carlo control	- Tempo	ral dif	ference
methods for con	ntrol.		

- 1. Implement iterative policy evaluation (C3).
- 2. Implement Monte Carlo methods for solving reinforcement learning tasks (C3).
- 3. Implement temporal difference methods for solving reinforcement learning tasks (C3).

Unit 3:Approximate Solution Methods; Policy Based Methods

Value prediction with function approximation - Gradient-descent methods - Linear methods - Control with function approximation.

Policy gradient - Actor-critic methods - Policy-based vs. value-based methods - Integrating supervised & reinforcement learning.

- 1. Implement function approximation methods for value prediction (C3).
- 2. Implement linear value function approximators (C3).
- 3. Explore integration of supervised and reinforcement learning (C5).

Learning 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 :		L				
Formative:					Summati	ve:	
Internal practical Test	t				Sessional	exan	nination
Theory Assignments					End seme	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	*	*	*	*		*
Laboratory examinati	on	*	*	*	*		*
Feedback Process	• Mic	d-Semes	ster feedl	oack			
	• Enc	d-Semes	ter Feed	back			
Reference Material	1. Reinford	cement L	earning:	An Introdu	ction, Richard	1 S. Sı	utton and Andrew
	G. Ba	rto, M	IT Pres	s, 2nd	Edition –	Avail	able online at
	https://v	veb.stanf	ford.edu/c	class/psych	209/Readings	s/Sutto	onBartoIPRLBoo
	k2ndEd	.pdf					
	2. Lecture	slides of	Prof. Em	ma Brunsk	till – Stanford	Univ	ersity – Available
	online a	ord.edu/cla	ss/cs234/sche	dule.l	ntml		
	3. Generati	ive Deep	Learning	: Teaching	Machines to	Paint,	Write, Compose,
	O'Reilly, 1	1st Edition, 20)19.				
	4. Reinford	earning and Optimal Control, Dimitri Bertsekas, Athena				Bertsekas, Athena	
	Scientif	ic; 1st E	dition, 20	19.			
Name of the Programs	<u>. </u>	ME	in Machi	ne Learnin	g		
Course Title:		App	lied Math	nematics fo	or Machine Le	arnin	g



Course Code:MCL 616 Cou				ourse Instructor:								
					nester:First Year, Semester 2							
No of Credits: 3						ereq	uisites	:MCL 6	601, 603,	605		
Synop	sis:		_				_				ation in a	
				-			tial for	r devel	oping an	d analys	ingstate o	of the art
		machine learning algorithms.										
Course	e											
Outco	mes	On suc	cessful	comple	etion	of t	his co	urse, st	udents w	ill be ab	le to	
(COs):												
CO		and app	ly them	to pract	tical p	orob	lems.				position to	-
CO	2:				_			_		_	plicability	
СО	3:				ivativ	es i	n macl	nine lear	ning and	understar	nd differen	t methods
		for com	_			1.1			.•		1.1	
CO	4:			• •	•				•	nization p		
со	5:	•						•	the princing librari	•	nind state-	of-the-art
Mappi	ng of (COs to 1	Pos									
COs	PO 1	PO 2	PO 3	PO 4	PO 5	5 1	PO 6	PO 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	ies:						ı	1	
Conten	ıt					Co	mpete	encies				
Unit 1	: Matr	ix Deco	mposit	ions an	d Ap	plio	cation	ıs				
Matrix	and	tens	or ni	oducts		1.	Deve	elop ide	as for m	atrix dec	ompositio	ons using
Determ		anc	•	race	_		bloc	k matrix	x represe	entations	(C5).	
Eigend					and	2.	Com	pare ar	nd contra	ast exact	and app	roximate
diagon	alizatio	on	_	Chole	eskv	decompositions in terms of construction and						
diagonalization - Cholesky						appli	ications	.				
decomposition - Singular value decomposition - Nonnegative matrix						3. Understand the optimization-centric view to						
factoriz	-	n - No	nnegat	ive ma	ttix		matrix factorization (C3).					
140111	Lanon.											



	4. Interpret the factors a	rising out of matrix			
	factorizations for real-lif	e problems (C3).			
Unit 2:Computing Derivatives					
Differentiability - Symbolic	1. Understand multivaria	able differentiability			
differentiation - Finite differences -	theory (C3).				
Automatic differentiation.	2. Understand the ba	sics of symbolic			
	differentiation (C3).				
	3. Develop ideas for appr	oximating derivatives			
	using finite differences (C5).			
	4. Understand the bas	sics of automatic			
	differentiation and con	mpare it with other			
	approaches (C3, C6).				
Unit 3:Continuous Optimization					
	4 77 1				
Optimization using gradient descent -	1. Understand the bas	ics of continuous			
Constrained optimization and Lagrange	optimization (C3).				
$multipliers Convex\ optimization - Sub$	2. Visualize constrained of				
gradients - Stochastic gradient descent -	and solutions in 3D (C3).				
Momentum methods.	3. Understand convexity a	and its importance in			
	machine learning (C3).				
	4. Understand gradient de				
	extensions for continuou	s optimization (C4).			
Learning strategies, contact hours and					
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						-	
TOTAL			44			74	
Assessment Methods	s:		•			•	
Formative:					Summati	ve:	
Internal practical Test	t				Sessional	exam	nination
Theory Assignments					End seme	ster e	xamination
Lab Assignment & V	iva				Viva		
Mapping of assessme	ent with Co	S			1		
Nature of assessment		CO 1	CO 2	CO 3	CO 4		CO 5
Sessional Examinatio	n 1	*	*				
Sessional Examinatio	n 2		*	*	*		
Assignment/Presentat	tion	*	*	*	*		*
End Semester Examin	nation	*	*	*	*		*
Feedback Process	• Mid	d-Semes	ster feedb	ack			
	• End	l-Semes	ster Feedl	back			
Reference Material							
Reference Material				_	·		isenroth, A Aldo
				_			from Cambridge
	book.pd	•	ss avanai	oie at mi	ps://ппп-000	ık.gım	ub.io/book/mml-
	_		ations, G	ene H. G	olub and C	harles	F. Van Loan,
		_		4th Edition			,
	12. Deep Le	earning,	Ian Good	fellow, Yo	shua Bengio,	, and	Aaron Courville,
MIT Press,2017. – Available online at http://www.deeplearningboo							earningbook.org/
	13. Understa	anding N	Machine L	earning: F	rom Theory	to Alg	gorithms (UML),
				Shai Ben-l	David, Camb	ridge	University Press,
	1st Edit	ion, 201	4.				

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



Academic Year: 2020-2021 Se					Seme	mester:First Year, Semester 2					
No of C	Credits:	: 1			Prere	equisites	:MCL 6	16			
Synop	sis:	mather	natical		ts esse	ntial fo		_		ation in a	
Course	<u> </u>										
Outcor (COs):	mes	On suc	cessful	comple	tion of	f this co	urse, stu	idents wi	ll be abl	le to	
CO 1:		Implem	ent and	compare	e matri:	x decom	position	technique	s.		
CO 2:		Assess	applicat	oility of 1	matrix	decompo	sition te	chniques	for pract	ical proble	ems.
CO 3:		Implem	ent and	compare	e differ	ent meth	ods for c	omputing	derivati	ves.	
CO 4:		_	Implement solutions for real-life problems formulated as a continuous optimization problem.								
CO 5:		Understand the implementations of state-of-the-art optimization algorithms used in machine learning libraries.						s used in			
Mappi	ng of (COs to 1	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				*	*						
		ent and	outcom	ies:							
Conten	ıt				(Compete	encies				
Unit 1	: Matr	ix Deco	mposit	ions an	d App	lication	S				
Matrix	and	tens	or pr	oducts	- 1	•			-	itions usi	ng block
Determ	ninant	anc	l t	race	- _		-	sentation		, 1	• .
Eigend	ecomp	osition		;	and 2	•		•		t and app	roximate
diagon			-	Chole	•		•	ons (C6).		undarata	nd tha
decom	positio	n -	Singul	ar va	lue	•	ement	codes		understa	
decom	positio	n - No	nnegati	ive ma	trix	-		-centric	view	7 to	matrix
factoriz	zation.					racto	rization	(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					
Optimization using gradient descent -	1.	Solve continuous optimiza	ation problems using		
Constrained optimization and Lagrange multipliers - Convex optimization – Sub		state of the art libraries (C	3).		
		Visualize constrained op	timization problems		
gradients - Stochastic gradient descent -		and solutions in 3D (C3).			
Momentum methods.	3.	Implement and visualize solutions of gradient			
		descent method and	its extensions for		
		continuous optimization (C4).		
	4.	Understand implementat	ions of continuous		
		optimization algorithms us	sed in state-of-the-art		
		libraries (C4).			
Learning strategies, contact hours and	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	5:						
Formative:					Summati	ive:	
Internal practical Test	t				Sessional	exam	ination
Theory Assignments					End seme	ester ex	xamination
Lab Assignment & 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	*	*	*	*		*
Laboratory examinati	on	*	*	*	*		*
Feedback Process	• Mic	d-Semes	ster feed	back	•		
	• End	d-Semes	ster Feed	lback			
Reference Material	1. Mathem	atics for	r Machin	e Learning	g by Marc Pe	eter De	eisenroth, AAldo
	Faisal,	and Ch	eng Soo	on Ong –	Online reso	ource f	From Cambridge
	Univers	ity Pres	ss availa	ible at ht	tps://mml-boo	ok.gith	ub.io/book/mml-
	book.pd						
		_					F. Van Loan,
					on edition, 20		A amon Caumvilla
	_	_			_		Aaron Courville, earningbook.org/
					-		gorithms (UML),
		· ·			·		University Press,
		ion, 201				-	-
Name of the Programs	<u> </u>	ME	in Machi	ine Learnir	ng		
Course Title:					essing Princip	oles & A	Applications



Academic Year: 2020-2021 Semester: First Year, Semester 2 No of Credits: 3 Prerequisites: MCL 601, 603						
No of Chaditas 2 Duamagnisitas MCI 601 602						
No of Credits: 5 Prerequisites: MCL 601, 603	Prerequisites:MCL 601, 603					
Synopsis: This course provides a thorough introduction to fundamental con	ncepts and	d modern				
algorithms in natural language processing.						
Course						
Outcomes On successful completion of this course, students will be able	to					
(COs):						
CO 1: Gain a thorough introduction to fundamental concepts and ideas in processing.						
CO 2: Develop an in-depth understanding of both algorithms for pro- information and the underlying computational properties of natural	language	es.				
CO 3: Analyse word-level, syntactic, and semantic processing from both a algorithmic perspective.	_	ic and an				
CO 4: Formulate deep learning approaches for natural language processing	g tasks.					
CO 5: Develop practical experience with state-of-the-art natural language processing tool and libraries.						
Mapping of COs to POs						
COs PO 1 PO 2 PO 3 PO 4 PO 5 PO 6 PO 7 PO 8 PO 9	PO 10	PO 11				
CO 1 *						
CO 2 * *						
CO 3 * * * *						
CO 4 * * * *						
CO 5 * * * * * * * *						
Course content and outcomes:						
Content Competencies						
Unit 1: Introduction to Natural Language Processing (NLP); Regular I	Express	ions; N-				
gram Language Models						
Terminology - Probability and NLP 1. Understand the basics of NI	LP and	role of				
probability in it (C3).						
Introduction to regular expressions - 2. Understand how to use and	d apply	regular				
Information extraction using regular expressions (C3).						
expressions. 3. Develop the idea of a probab	bilistic 1	anguage				
model (C5).		<i>6</i> 63				



Proba	bilistic	language	model - Chai	in
rule	and	Markov	assumption	-
Evalu	ating	language	models	_
Smoo	thing.			

4. Understand how to evaluate and compare language models (C6).

Unit 2:Naive Bayes and Sentiment Classification; Vector Semantics and Embeddings

Vector ser	mantics - V	Vords	and vectors -
Cosine fo	r measurii	ng sin	nilarity - TF-
IDF vecto	r model - V	Word2	2Vec &
GloVe	models	-	Visualizing
embeddin	gs.		

- 1. Understand how to perform sentiment classification (C4).
- 2. Develop ideas for vector representation of words (C5).
- 3. Understand and compare vector models for words (C6).
- 4. Understand how to visualize word embeddings (C3).

Unit 3:NLP with Deep Learning; Applications of Natural Language Processing

Neural language models - Introduction
to PyTorch -Sequence processing with
recurrent neural networks

- 1. Understand how deep learning can be used for NLP applications (C3).
- 2. Gain experience in using PyTorch (C3).
- 3. Understand how recurrent neural networks can be used for NLP applications (C4).
- 4. Explore practical applications of NLP (C3).

Learning 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					74		
5:		•					
				Summativ	ve:		
-				Sessional of	examination		
Theory Assignments				End semes	ster examination		
Lab Assignment & Viva				Viva			
ent with Co	S						
	CO 1	CO 2	CO 3	CO 4	CO 5		
n 1	*	*					
Sessional Examination 2				*			
Assignment/Presentation			*	*	*		
nation	*	*	*	*	*		
• Mic	d-Semes	ster feedl	oack				
• End	d-Semes	ster Feed	back				
-		-	_	•			
			`	•	ailable online at		
•			•	•	solveing Toyt with the		
			-	•			
ISTE					vailable online at		
https://v	www.nltl						
3. A Prime	er on Ne	ural Netw	ork Mode	els for Natural	Language Processing,		
Yoav	Go	ldberg	_	Available	online at		
http://fa	culty.cs	e.tamu.ed	u/huangrh/	Spring18/nnlp	o.pdf		
	_	_	_	•	Delip Rao & Brian		
McMah	an,O'Re	illy, 1st E	dition, 201	19.			
	ent with Co n 1 n 2 ion nation • Mie • Enc 1. Speech Pearson https://v 2. Natural Natural ISTE https://v 3. A Prime Yoav http://fa 4. Natural	ent with Cos CO 1 n 1	ent with Cos CO 1 CO 2 n 1 * * n 2 * ion * * Mid-Semester feedle End-Semester Feed 1. Speech and Language Properson; 3rd Edition https://web.stanford.edu/- 2. Natural Language Proces Natural Language Toolking ISTE Ltd., 1st Editor https://www.nltk.org/bool 3. A Primer on Neural Network Yoav Goldberg http://faculty.cse.tamu.edu 4. Natural Language Proces	ent with Cos CO 1 CO 2 CO 3 n 1 * * n 2 * * ion * * * • Mid-Semester feedback • End-Semester Feedback 1. Speech and Language Processing, Pearson; 3rd Edition (drafthttps://web.stanford.edu/~jurafsky/s 2. Natural Language Processing with Natural Language Processing with Natural Language Toolkit, Steven E ISTE Ltd., 1st Edition, 2 https://www.nltk.org/book/ 3. A Primer on Neural Network Mode Yoav Goldberg — http://faculty.cse.tamu.edu/huangrh. 4. Natural Language Processing with	Summative End semestry CO 1 CO 2 CO 3 CO 4 In 1 * * * In 2 * * * In ation * * * Mid-Semester feedback End-Semester Feedback End-Semester Feedback I. Speech and Language Processing, Dan Jurafsky Pearson; 3rd Edition (draft) — Av https://web.stanford.edu/~jurafsky/slp3/ Z. Natural Language Processing with Python. — An Natural Language Toolkit, Steven Bird, Ewan Kle ISTE Ltd., 1st Edition, 2017 — Ar https://www.nltk.org/book/ 3. A Primer on Neural Network Models for Natural		

Name of the Program:	ME in Machine Learning
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Course Title:					Natural Language Processing Principles and Applications						
	TOT 61	77									
		2021						2			
			• 1		_						
:		-			_	•	onal found	dation to	the applic	cations of	
	algorith	ms for r	iaturai ia	ınguage	processi	ing.					
es	On suc	cessful	comple	tion of	this cou	ırse, stu	dents wi	ll be abl	e to		
		_	n introd	action to	fundan	nental co	oncepts a	nd ideas	in natural	language	
	-		•		•		•	•	•	•	
				• •	•	•	_				
						Pro		Jou		wii	
	Formulate deep learning approaches for natural language processing tasks.										
	Develop practical experience with state-of-the-art natural language processing tools and libraries.										
of C	COs to 1	Pos									
01	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	
	*	*		*							
	*	*		*							
	*	*	*	*							
	*	*	*	*							
			*	*							
onte	nt and	outcom	es:								
				C	ompeter	ncies					
ntro	duction	to Nat	tural L	anguag	ge Proc	essing	(NLP); I	Regular	Express	ions; N-	
ngua	ige Mod	lels									
	ge Moo		d NLP	1.	Unde	rstand	the basi	cs of N	NLP and	role of	
			d NLP	1.					NLP and	role of	
ogy -		oility an			proba	bility in	n it (C3).			role of	
ogy -	- Probat to regu	oility an	oression		proba Unde	bility in	n it (C3).				
	ode:N Yea dits:	Gain a process Developinformal Analyse algorith Formula Develop and libr of COs to 1 // PO 2 * * * * ontent and of the content and of the c	de:MCL 617L Year: 2020-2021 dits: 1 This course pralgorithms for residual algorithms for residual processing. Develop an ininformation and Analyse word-lealgorithmic persection and libraries. of COs to Pos O 1 PO 2 PO 3 * * * * * * ontent and outcome.	dis: 1 This course provides algorithms for natural lass On successful comples Gain a thorough introdust processing. Develop an in-depth usinformation and the understand Analyse word-level, synalgorithmic perspective. Formulate deep learning. Develop practical expensand libraries. of COs to Pos O 1 PO 2 PO 3 PO 4 * * * * * * * * * ontent and outcomes:	dits: 1 This course provides a thoroalgorithms for natural language Some of Costo Pos O1 PO 2 PO 3 PO 4 PO 5 * * * * * * * * * * * * * * * * * * * * * * * * * * *	Develop practical experience with state and libraries. Ode:MCL 617L Year: 2020-2021 Semester:First Prerequisites: This course provides a thorough coralgorithms for natural language processions. On successful completion of this councillates of the councillate of the councill	Develop an in-depth understanding of both information and the underlying computational gorithmic perspective. Formulate deep learning approaches for natural Develop practical experience with state-of-the-and libraries. Of COs to Pos Lab Course Instructor:	de:MCL 617L Year: 2020-2021 Semester:First Year, Semester 2 dits: 1 Prerequisites:MCL 617 This course provides a thorough computational found algorithms for natural language processing. Son successful completion of this course, students wire processing. Develop an in-depth understanding of both algorithm information and the underlying computational properties. Analyse word-level, syntactic, and semantic processing for algorithmic perspective. Formulate deep learning approaches for natural language. Develop practical experience with state-of-the-art natural and libraries. of COs to Pos O 1 PO 2 PO 3 PO 4 PO 5 PO 6 PO 7 PO 8 * * * * * * * * * * * * * * * * * *	Develop an in-depth understanding of both algorithms for prinformation and the underlying computational properties of natural language processing. Develop an in-depth understanding of both algorithms for both algorithmic perspective. Formulate deep learning approaches for natural language processing. Develop practical experience with state-of-the-art natural language and libraries. Of COs to Pos O 1 PO 2 PO 3 PO 4 PO 5 PO 6 PO 7 PO 8 PO 9 * * * * * * * * * * * * * * * * * *	Lab Ode: MCL 617L Course Instructor: Year: 2020-2021 Semester: First Year, Semester 2 dits: Prerequisites: MCL 617 This course provides a thorough computational foundation to the applic algorithms for natural language processing. Somester: First Year, Semester 2 Prerequisites: MCL 617 This course provides a thorough computational foundation to the applic algorithms for natural language processing. Somester: First Year, Semester 2 Prerequisites: MCL 617 This course provides a thorough computational foundation to the applic algorithms for natural language processing. Gain a thorough introduction to fundamental concepts and ideas in natural processing. Develop an in-depth understanding of both algorithms for processing information and the underlying computational properties of natural language Analyse word-level, syntactic, and semantic processing from both a linguist algorithmic perspective. Formulate deep learning approaches for natural language processing tasks.	



Proba	bilistic	language	model - Chain			
rule	and	Markov	assumption	-		
Evaluating		language	models	_		
Smoo	thing.					

- 3. Develop the idea of a probabilistic language model (C5).
- 4. Understand how to evaluate and compare language models (C6).

Unit 2:Naive Bayes and Sentiment Classification; Vector Semantics and Embeddings

Vector semantics - Words and vectors -								
Cosine for measuring similarity - TF-								
IDF vector model - Word2Vec &								
GloVe models - Visualizing								
embeddings.								

- 1. Implement sentiment classification using reallife datasets (C3).
- 2. Implement building blocks for vector representation of words (C5).
- 3. Implement and compare vector models for words (C6).
- 4. Visualize word embeddings (C3).

Unit 3:NLP with Deep Learning; Applications of Natural Language Processing

Neural language models - Introduction						
to PyTorch -Sequence processing with						
recurrent neural networks						

- Implement neural models for NLP applications (C3).
- 2. Gain experience in using PyTorch (C3).
- 3. Implement recurrent neural network models for NLP applications (C3).
- 4. Explore practical applications of NLP (C3).

Learning 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	48			-	
Assessment Methods	5:							
Formative:					Summative:			
Internal practical Test	,				Sessional examination			
Theory Assignments					End seme	ster e	xamination	
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 Examinatio	n 1	*	*					
Sessional Examinatio	n 2			*	*		*	
Assignment/Presentat	ion	*	*	*	*		*	
Laboratory examination	on	*	*	*	*	*		
Feedback Process	Mid-Semester feedback							
	• End	d-Semes	ter Feed	back				
Reference Material	1. Speech	and Lan	guage Pr	ocessing,	Dan Jurafsky	and J	ames H. Martin,	
	1. Speech and Language Processing, Dan Jurafsky and James H. Martin, Pearson; 3rd Edition (draft) – Available online at							
	https://v	veb.stanf	ford.edu/	~jurafsky/s	slp3/			
	2. Natural Language Processing with Python. – Analysing Text with the							
	Natural Language Toolkit, Steven Bird, Ewan Klein, and Edward Loper,							
	ISTE Ltd., 1st Edition, 2017 - Available online at							
	https://www.nltk.org/book/							
	3. A Primer on Neural Network Models for Natural Language Processing,							
Yoav Goldberg – Available online							online at	
	http://faculty.cse.tamu.edu/huangrh/Spring18/nnlp.pdf							
	4. Natural Language Processing with PyTorch, Delip Rao & Brian McMehan O'Beilly, 1st Edition, 2010							
	McMahan,O'Reilly, 1st Edition, 2019.							



Name of the Program: ME					ME	ME in Machine Learning						
O .					Convolutional Neural Networks for Computer Vision							
					Course Instructor:							
				Sem	ester:Firs	st Year,	Semester 2	2				
No of C	Credits:	: 3			Prei	requisites	:MCL 6	601, 603				
Synops	sis:	This co	ourse p	rovides	a the	oretical fo	oundatio	on for the a	application	on of conv	olutional	
		neural networks to computer vision.										
Course	9											
Outcor	mes	On successful completion of this course, students will be able to										
(COs):												
CO	1:	Underst	and the	differe	nce bet	ween ima	ige proc	essing and	compute	er vision.		
СО	2:	Understand the theory behind CNNs and to gain hands-on experience on the application of CNNs in computer vision.										
CO	3:	Analyse a real-life problem involving computer vision and solve it using CNNs.								INs.		
CO	4:	Decide	how to	choose	an exis	sting CNN	V archite	cture for a	n applica	ation probl	em.	
CO	5:	Develop	praction praction	cal expe	rience	with state	e-of-the-	art deep le	arning to	ools and lil	oraries.	
Mappi	ng of (COs to 1	POs									
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	
CO 1	*											
CO 2	*	*	*									
CO 3		*	*		*							
CO 4		*	*	*	*							
CO 5		*	*	*	*	*			*			
Course	conte	ent and	outcon	nes:		•	•		•	•		
Conten	ıt					Compete	encies					
Unit 1: Introduction to Computer Vision; Features; Neural Networks Basics												
Compu	iter vis	sion ove	rview -	Histo	rical	1. Com	pare a	nd contra	st com	puter vis	sion and	
context and applications - Image image processing (C6).												
processing vs. computer vision						2. Understand how to build features in the context						
Histogram of oriented gradients (HOG)						of computer vision (C4).						
- Scale-invariant feature transform						3. Compare and contrast different types of						
							features for computer vision (C6).					
(SURF) -	Limitat	ions	of h	and-	4. Extend ideas from neural networks to computer						
engineered features.						vision (C2).						



Multi-layer perceptron: architecture and						
parameter learning.						
Unit 2:Convolutional Neural Networks	s (CNN)					
Network layers: pre-processing,	1. Understand the building blocks of a CNN (C4)					
convolutional layers, pooling layers,	2. Understand the purpose and interconnectivity					
nonlinearity, fully connected layers,	of different types of CNN layers (C4).					
region of interest pooling - Loss	3. Understand the role of nonlinear activation					
functions: hinge loss, squared hinge	functions in a CNN (C4).					
loss, cross-entropy loss, Euclidean loss,	4. Understand different types of loss functions					
L1 error.	used in a CNN (C4).					
Unit 3:CNN Learning; Visualizing and	l Understanding CNNs					
Weight initialization – Regularization - Gradient based learning: batch-, stochastic-, and mini-batch gradient descent, gradient computations in CNN. Unit 4:CNN Architectures; Application	 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). 					
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						
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 Learnin	ig (PBL)		02			04	
Case Based Learning (C	CBL)		-		-		
Revision	02			-			
Assessment	06			-			
TOTAL		44			74		
Assessment Methods:							
Formative:				Summati	ve:		
Internal practical Test					Sessional	exam	ination
Theory Assignments					End seme	ster e	xamination
Lab Assignment & Viv	a				Viva		
Mapping of assessmen	nt with Cos	S			l		
Nature of assessment	CO 1	CO 2	CO 3	CO 4		CO 5	
Sessional Examination	1	*	*				
Sessional Examination	2		*	*	*	*	
Assignment/Presentation	n	*	*	*	*	* *	
End Semester Examina	tion	*	*	*	*		*
	End 1. A Guide Khan, I Bennam 2. Lecture s at http:// B. Neural N Press http://ne 4. Compute	to Conv Hossein doun, Mo slides of /cs231n.s Networks euralnetwer Vision r, 2011	Rahman organ & C Prof. Fei- stanford.es and De - vorksande on: Algo - Onl	Neural Ne	Afaq Ali Shablishers, 201 anford University, Michael Mable ag.com/index.dd Applicatio	nah, a 8. rsity – Nielser onl html	er Vision, Salman and Mohammed Available online at tichard Szeliski, er available at



Name of the Program: M				ME	ME in Machine Learning							
Course	Title:				Cor	Convolutional Neural Networks for Computer Vision Lab						on Lab
Course	Code:	MCL 61	8L		Cor	Course Instructor:						
Acader	nic Yea	ar: 2020	-2021		Sen	nest	er:First	Year, Semester 2				
No of (Credits	: 1			Pre	requ	uisites:N	ICL 618	3			
Synop	-										ation of	
		convol	utional ne	eural net	wor	ks to	comput	er vision	1.			
Course	e											
Outco	mes	On suc	ccessful	complet	tion	of t	his cour	se, stud	lents wi	ll be abl	le to	
(COs):	}											
CO 1:		Implement image processing and computer vision tasks.										
CO 2:		Apply CNNs for computer vision problems.										
CO 3:		Analyse a real-life problem involving computer vision and solve it using CNNs.								INs.		
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.						braries.				
Mapping of COs to Pos												
COs	PO 1	PO 2	PO 3	PO 4	PO) <i>5</i>	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11
CO 1	*	*	*		*							
CO 2	*	*	*		*							
CO 3	*	*	*	*	*							
CO 4	*	*	*	*	*							
CO 5				*	*					*		
		ent and	outcom	es:								
Conter	ıt					Co	mpeten	cies				
Unit 1	: Intro	duction	to Con	puter `	Visi	on;	Featur	es; Neu	ral Net	works l	Basics	
Compu	iter vis	sion ove	erview -	Histori	cal	1.	Impler	nent ba	sic cor	nputer	vision an	d image
contex	t and	applic	cations	- Ima	ige		proces	sing tas	ks (C3)			
process	sing vs	. compu	iter visio	n		2.	Build	features	in the c	ontext o	of comput	er vision
Histog	ram of	oriente	d gradie	nts (HO	G)		(C3).					
- Sca	le-inva	riant f	feature	transfo	rm	3.	Compa	are an	d cont	rast di	fferent t	ypes of
(SIFT) - Speeded-up robust features features for computer vision (C6).								es for co	mputer	vision ((C6).	



NSPIRED BY LIFE (Deemed to	be Un	iversity under Section 3 of the UGC Act, 1956)	
(SURF) - Limitations of hand-	4.	Implement and extend	ideas from neural
engineered features.		networks to computer vision	on (C3).
Multi-layer perceptron: architecture and			
parameter learning.			
Unit 2:Convolutional Neural Networks	s (C	CNN)	
Network layers: pre-processing,	1.	Visualize and understand t	he building blocks of
convolutional layers, pooling layers,		a CNN (C4).	
nonlinearity, fully connected layers,	2.	Implementdifferent types	of CNN layers and
region of interest pooling - Loss		understand their utility (C4	4).
functions: hinge loss, squared hinge	3.	Implement different n	onlinear activation
loss, cross-entropy loss, Euclidean loss,		functions, compare and co	ntrast them (C6).
L1 error.	4.	Implement and understand	the role of different
		types of loss functions use	d in a CNN (C4).
Unit 3:CNN Learning; Visualizing and	l Uı	nderstanding CNNs	
Weight initialization – Regularization -	1.	Implement random initializ	zation of weights in a
Gradient based learning: batch-,		CNN and compare it	with a non-random
stochastic-, and mini-batch gradient		initialization (C6).	
descent, gradient computations in CNN.	2.	Implement regularization t in CNNs (C3).	o prevent overfitting
	3.	Implement different gradie	ent-based approaches
		for optimization (C3).	
	4.	Implement efficient gradi	ent computations in
		CNNs (C4).	
Unit 4:CNN Architectures; Application	ns (of CNNs in Computer Vision	on
Image classification, Object detection	1.	Explore the building bloc	ks 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	stı	ident learning time	
Learning strategy		Contact hours	Student learning

time (Hrs)



Lecture			12			-		
Seminar			-			-		
Quiz			-		-			
Small Group	Discussion (SGD)		-		-			
Self-directed	d learning (SDL)		-			-		
Problem Bas	sed Learning (PBL)		-		-			
Case Based	Learning (CBL)		03			-		
Clinic			-			-		
Practical			24			-		
Revision			03			-		
Assessment			06			-		
TOTAL						-		
Assessment	Methods:		I .					
Formative:					Summati	ummative:		
Internal prac	ctical Test				Sessional	examination		
Theory Assi	gnments				End seme	ster examination		
Lab Assignr	nent & Viva				Viva			
Mapping of	assessment with Co	S			1			
Nature of as	sessment	CO 1	CO 2	CO 3	CO 4	CO 5		
Sessional Ex	xamination 1	*	*					
Sessional Ex	xamination 2			*	*	*		
Assignment	Presentation	*	*	*	*	*		
Laboratory 6	examination	*	*	*	*	*		
Feedback	Mid-Semeste	er feedba	ack	-[1		
Process	• End-Semeste	er Feedb	ack					
Reference	A Guide to Convo	olutional	Neural N	Networks f	or Computer	Vision, Salman Khan,		
Material					-	Bennamoun, Morgan &		
	Claypool Publishe	ers, 2018.	•					
	2. Lecture slides of	Prof. Fe	ei-Fei Li	- Stanford	d University	- Available online at		
	http://cs231n.stan	ford.edu/						
	3. Neural Networks	and Dee	ep Learn	Learning, Michael Nielsen, Determination Press -				
	http://neuralnetwo	orksandde	eeplearnii	ng.com/ind	ex.html			



4. Computer Vision: Algorithms and Applications, Richard Szeliski, Springer, 2011											
Name of the I	Program	:		ME	ME in Machine Learning						
Course Title:				Enti	repreneurs	ship					
Course Code:	ENP 60	1		Cou	ırse Instr	uctor:					
Academic Ye		-2021					emester 2				
No of Credits	•				requisites						
Synopsis:	This co	ourse in	troduce	es stud	dents to tl	ne theory	of entrep	reneurshi	p and its p	ractical	
	implen	nentatio	on. It f	ocuse	es on dif	ferent st	ages rela	ted to th	e entrepr	eneurial	
	process, including business model innovation, monetization, small busines										
	management as well as strategies that improve performance of new business										
ventures. Centred on a mixture of theoretical exploration as well as case studies									studies		
of real-world examples and guest lectures, students will develop an understanding									standing		
of successes, opportunities and risks of entrepreneurship. This course has an									has an		
interdisciplinary approach and is therefore open to students from other Majors.								Iajors.			
Course											
Outcomes	Outcomes On successful completion of this course, students will be able to:										
(COs):											
CO 1	Unders			es of e	entrepren	eurial sk	ills and co	ompetenci	ies for cre	ation of	
CO 2	Familia enhance					overview	of entrep	oreneursh	ip with a	view to	
CO 3	Apprai	se the	entrepre	eneuri	ial proces	s starting	g with pre	-venture s	stage.		
CO 4	Create	and ex	ploit in	novat	ive busin	ess ideas	and marl	ket opport	tunities.		
CO 5	Build a			using	on develo	oping no	vel and u	nique app	roaches to	market	
Mapping of	COs to	POs									
COs PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	
CO 1 *											
CO 2			*								
CO 3		*									
CO 4					*						
CO 5							*				
Course cont	ent and	outcon	nes:	1	1	1	1	1	1	1	
Content					Compete	encies					



Unit 1: Introduction to Entrepreneursh	ıip
Meaning and Definition of	1. Explain the meaning of Entrepreneurship
Entrepreneurship-Employment vs	(C1).
Entrepreneurship, Theories of	2. Discuss the theories of Entrepreneurship (C1).
Entrepreneurship, approach to	3. Discuss the approaches to Entrepreneurship
entrepreneurship, Entrepreneur	(C1).
vs.Manager	
Unit 2: Entrepreneurial Traits	
Personality of an entrepreneur, Types of	1. Discuss the personality traits of entrepreneurs
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 distinctive
	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 (C1).
Environment, Macro and Micro	2. Develop creativity and critical thinking in
analysis	identifying opportunities (C5).
	3. Apply innovative approaches in envisioning
	one's entrepreneurial career (C3).
Unit 5: Business Plan Writing	
Points to be considered, Model	1. Identify different business models (C3).
Business plan	2. Describe various 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).



and s	help char. Student lear Contact h 30 02 02 - 02 - 02	acteristics ar		_	learning		
and s	Contact h 30 02 02 - 02 -	ning time	nd compo	Student time (Hrs) 60 04 02 04	learning		
and s	Contact h 30 02 02 - 02 -			time (Hrs) 60 04 02 04			
	30 02 02 - 02 -	ours		time (Hrs) 60 04 02 04			
	02 02 - 02 -			60 04 02 04			
	02 02 - 02 -			04 02 04			
	02 - 02 -			02			
	- 02			04			
	02						
	-			04			
				· .			
	02			-			
	02			-			
Assessment				-			
	44			74			
		Summa	tive:				
		Session	Sessional examination				
		End sen					
		Viva					
) 1	CO 2	CO 3	CO 4	CO 5	CO 6		
	*						
		*	*				
				*	*		
	*	*	*	*	*		
mest	ter feedback						
	mes	0 1 CO 2 * mester feedback	Summa Session End sen Viva 1 1 CO 2 CO 3 * *	Summative: Sessional exami End semester ex Viva O 1 CO 2 CO 3 CO 4 * * * * * * * * * * * * *	Summative: Sessional examination End semester examination Viva 1 CO 2 CO 3 CO 4 CO 5 * * * * * * * * * mester feedback		



Reference Material	1.	NVR	Naidu	and	T.	Krishna	Rao,	"Management	and			
		Entrep	reneurshi	p", IK	Inter	national Pu	blishing	g House Pvt. Ltd 2	2008.			
	2.	Mohan	Mohanthy Sangram Keshari, "Fundamentals of Entrepreneurship",									
		PHI Pu	PHI Publications, 2005									
	3.	Butler, D. (2006). Enterprise planning and development. USA:										
		Elsevie	er Ltd. (Gerber,	M.I	E. (2008)	Awaker	ning the entrepre	eneur			
		within.	NY: Ha	rper Co	ollins							



Name o	me of the Program: ME in Machine Learning											
Course	Title:				Entrep	Entrepreneurship Lab						
Course	Code:	ENP 601	L		Cours	se Instruc	tor:					
		r: 2020-	2021		Seme	ster:First	Year, Se	emester 2	2			
No of C	Credits	: 1			Prere	quisites:N	ICL 618	8				
Synop	sis:	This course introduces students to the theory of entrepreneurship and its practical implementation. It focuses on different stages related to the entrepreneurial process, including business model innovation, monetization, small business management as well as strategies that improve performance of new business ventures. Centred on a mixture of theoretical exploration as well as case studies of real-world examples and guest lectures, students will develop an understanding of successes, opportunities and risks of entrepreneurship. This course has an interdisciplinary approach and is therefore open to students from other majors.										
Course Outcon (COs):	mes	On successful completion of this course, students will be able to										
CO 1		Understand the basics of entrepreneurial skills and competencies for creation of new ventures.										
CO 2		Familiarize with the concept and overview of entrepreneurship with a view to enhance entrepreneurial talent.										
CO 3						process						
CO 4		Build		set foc		e busines on devel						
Mappi	ng of	COs to	POs									
COs	PO 1	PO 2	PO 3	PO 4	PO 5	5 PO 6	PO 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						Competen	cies					
			to Enti									
Meaning and Definition of 1. Explain the meaning of Entrepreneurship Entrepreneurship-Employment vs (C1).								the mea	aning o	of Entrep	oreneurship	



Entrepreneurship, Theories of	2. Discuss the theories of Entrepreneurship (C1).
Entrepreneurship, approach to	3. Discuss the approaches to Entrepreneurship
entrepreneurship, Entrepreneur	(C1).
vs.Manager	
Unit 2: Entrepreneurial Traits	
Personality of an entrepreneur, Types of	1. Discuss the personality traits of entrepreneurs
Entrepreneurs	(C2).
Unit 3: Process of Entrepreneurship	
Factors affecting Entrepreneurship	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 distinctive
	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 (C1).
Environment, Macro and Micro	2. Develop creativity and critical thinking in
analysis	identifying opportunities (C5).
	3. Apply innovative approaches in envisioning
	one's entrepreneurial career (C3).
Unit 5: Business Plan Writing	
Points to be considered, Model	1. Identify different business models (C3).
Business plan	2. Describe various 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
	characteristics and competencies (C5).
Learning strategies, contact hours and st	<u> </u>

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:					1		
Formative:				Summative:			
Internal practical Test				Sessional examination			
Theory Assignments				End semester examination			
Lab Assignment & Viva				Viva			
Mapping of assessment with Co	os						
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 • Mi	d-Semes	ster feed	back	1	1		
• En	d-Semes	ster Feed	lback				



Reference Material	1.	VR Naidu and T. Krishr	a Rao, "Management and
		ntrepreneurship", IK Internation	nal Publishing House Pvt. Ltd
		008.	
	2.	Iohanthy Sangram Keshari, "Fun	damentals of Entrepreneurship",
		HI Publications, 2005	
	3.	utler, D. (2006). Enterprise pla	nning and development. USA:
		lsevier Ltd. Gerber, M.E. (2008)	3) Awakening the entrepreneur
		rithin. NY: Harper Collins.	



Name o	of the P	rogram	•		ME	in Machi	ne Learnii	ng							
Course					Mir	ni Project -	- 2								
		MCL 69				Course Instructor:									
		ar:2020 -	-2021			Semester:First Year, Semester 2									
No of (Prerequisites: Programming in Python / R									
Synop	sis:			•		to select a problem in the area of their interest and the									
		area of	their s	pecializ	zation	tion that would require an implementation in hardware /									
		softwa	re or bo	oth in a	seme	emester									
Cours	e														
Outco	mes	On suc	cessful	compl	etion	of this co	urse, stu	dents wil	l be abl	e to					
(COs)	•														
CO	1	Apply	the obj	ectives	of th	e project	work and	l provide	an ade	quate bac	kground				
CO	, 1	with a	detaile	d litera	ture s	urvey									
Breakdown the project into sub blocks with sufficient details to allo											the work				
CO	02	to be re	eproduc	ced by	an inc	lependent	research	ier							
CO	. 2	Compo	ose hard	dware/s	oftwa	are design	, algorith	nms, flov	vchart,	methodol	ogy, and				
CO	3	block o	diagran	1											
CO	4	Evalua	te the r	esults											
CO	5	Summ	arize th	e work	carri	ed out									
Mappi	ing 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							*								
Cours	e conte	ent and	outcon	ies:	I										
Conte	ıt					Compet	encies								
Phase															
Proble	m i	dentific	ation,	sync	psis	At the e	nd of the	topic stu	ident sh	ould be a	ble to:				
submission, status submission, mid						1. Identify the problem/specification (C1)									
evalua	tion.					2. Discuss the project (C2)									



(Deemed	d to be University under Section 3 of the UGC Act, 1956)
	3. Prepare the outline (C3)
	4. Describe the status of the project (C2)
	5. Prepare a mid-term project presentation report
	(C3)
	6. Prepare and present mid-term project
	presentation slides (C3, C5)
	7. Develop project implementation in
	hardware/software or both in chosen platform
	(C5)
Phase 2	
Status submission, final evaluation.	1. Prepare the progress report (C3)
	2. Prepare the final project presentation report
	(C3)
	3. Prepare and present final project presentation
	slides (C3, C5)
	4. Modify and Develop implementation in
	hardware/software or both in chosen platform
	(C3, C5)
	5. Justify the methods used and obtained results
	(C6)
Learning strategies, contact hours an	nd 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:					Summativ	ve:		
Project Problem Selec	tion				Mid-Term	Presentation		
Synopsys review					atus review			
First status review					Demo & F	Final Presentation		
Mapping of assessme	ent with Cos							
Nature of assessment	C	O 1	CO 2	CO 3	CO 4	CO 5		
Mid Presentation	*		*					
Presentation	*		*	*	*	*		
Feedback Process	emest	ter Feedb	oack	1				
Reference Material	Particular to the	he ch	osen pro	ject				



Name	of the P	rogram	:		ME i	n Machi	ne Learni	ng							
Course	Title:				Semi	nar - 2									
		MCL 69				se Instr									
		r:2020 -	-2021					emester 2							
No of (Prerequisites: Communication Skill										
Synop	sis:	1. To	select,	search	and learn technical literature.										
		2. To	Identif	y a cur	rent and relevant research topic.										
		3. To	prepare	e a topi	c and deliver a presentation.										
		4. To	develo	p the sl	xill to a	uthor a	technica	l report.							
		5. De	velop a	bility to	o work	in grou	ps to rev	iew and	modify t	technical	content.				
Cours	e	On successful completion of this course, students will be able to													
Outco	mes	On suc	ccessful	compl	etion o	f this co	ourse, stu	dents wi	ll be abl	e to					
(COs)	:														
CO 1		Show	compet	ence in	identif	ying rel	evant inf	formation	n, definii	ng and ex	plaining				
COI		topics under discussion.													
CO 2		Show	compet	ence in	workir	ng with	a method	lology, st	tructurin	g their oral work,					
CO 2		and sy	nthesiz	ng info	ormatio	n.									
CO 3		Use ap	propria	te regi	sters ar	nd voca	bulary, a	nd will	demonst	rate com	mand of				
COS		voice i	modula	ion, vo	oice pro	jection,	and pac	ing.							
CO 4		Demoi	nstrate	that the	ey have	paid c	lose atte	ntion to	what ot	hers say	and can				
CO 4		respon	d const	ructive	ly.										
		Develo	op pers	uasive	speec	h, pres	ent info	rmation	in a c	ompellin	g, well-				
CO 5		structu	red, an	d logica	al seque	ence, re	spond re	spectfull	y to opp	osing ide	as, show				
COS		depth	of kno	wledg	e of c	omplex	subject	s, and	develop	their al	oility to				
		synthe	size, ev	aluate	and ref	lect on i	nformati	on.							
Mappi	ing of (COs to	POs												
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11				
CO 1	*							*	*		*				
CO 2	*							*	*		*				
CO 3	*							*	*		*				
CO 4	*							*	*		*				
CO5	*							*	*		*				
		1				İ			1	<u>l</u>					

Learning strategy			Contact	hours		Studen	t learning		
						time (H	Hrs)		
Lecture			-						
Seminar			-			-			
Quiz			-			-			
Small Group Discussi	on (SGD)		14			-			
Self-directed learning	(SDL)		-			-			
Problem Based Learn	ing (PBL)		-			-			
Case Based Learning	Case Based Learning (CBL)					-			
Clinic		-			-				
Practical		-		-					
Revision			-			-			
Assessment			-			-			
TOTAL			14		-				
Assessment Methods	10								
Formative:	'•				Summa	ativo.			
Seminar Topic Select	ion				Summe	auve.			
Synopsys review									
PPT Review									
111 Keview									
Mapping of assessme	ent with Co	s							
Nature of assessment		CO 1	CO 2	CO 3	CO 4	CC) 5		
Presentation		*	*	*	*	*			
Feedback Process	• Enc	l-Semest	er Feedba	 ck	<u> </u>				
	- Dire	. 50111050					_		
Reference Material	o the che	e chosen Seminar							



0						in Machin	ne Learnir	ng						
Course	Title:				Pro	ject Work								
		MCL 79				Course Instructor:								
		r:2020 -	-2021			Semester: Second Year, Semesters 3, 4								
No of C	Credits:	: 25				Prerequisites: SDLC, communication skills, technical skills.								
Synop	sis:	The pr	roject v	work a	ims t	ns to challenge the student's analytical and creative								
		abilitya	and to a	llow th	e stu	student to synthesize ideas, apply expertise, and insight								
		learned	l in the	studen	t'scor	e discipli	ne.							
		Studen	ts buil	ld self	-conf	idence, c	demonstr	ate inde	penden	ce, and	develop			
		profess	sionalis	m on s	ucces	sfully cor	npletion	of the pr	oject.					
Course	e													
Outco	mes	On suc	cessful	compl	etion	of this co	urse, stu	dents wil	ll be abl	e to				
(COs):	:													
		Succes	sfully a	cquain	t with	ı a workir	ng enviro	nment aı	nd proc	esses that	are in			
CO) 1	place a	t releva	ant indu										
CO	2	Familia	arize w	ith the	challe	enges as r	elevant p	rofession	nals.					
CO	3	Reviev	v literat	ure and	d deve	elop solut	ions for 1	eal time	onboar	d projects	S.			
CO	4	Author	techni	cal rep	ort an	d deliver	presentat	tion.						
CO	5	Apply	engine	ering a	nd ma	nagemen	t principl	les to ach	nieve pr	oject goa	1.			
Mappi	ng of (COs to	Pos											
COs	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11			
CO 1						*	*	*	*	*	*			
CO 2					*									
CO 3	*	*	*	*	*									
CO 4	*	*	*	*										
CO5:						*	*	*	*	*	*			
Course	e conte	ent and	outcon	ies:	•			•		•				
Conten	ıt					Compete	encies							
Phase														
Proble	m i	dentifica	ation,	sync	psis	At the end of the topic student should be able to:								
submis	sion,	status	submis	ssion,	mid	id 1. Identify the problem/specification (C1).								
evaluat	tion.					2. Disc	uss the p	roject (C	22).		_			



3.	Prepare the outline (C3).								
4.	Prepare a mid-term project	ct presentation report							
	(C3).								
5.	Prepare and present	mid-term project							
	presentation slides (C3, C5).								
6.	Develop project in	mplementation in							
	hardware/software or both	h in chosen platform							
	(C5).								
1									
1.	Prepare the progress repor	rt (C3).							
2.	Prepare the final project	presentation report							
	(C3).								
3.	Prepare and present final	project presentation							
	slides (C3, C5).								
4.	Modify and develop	implementation in							
	hardware/software or both	h in chosen platform							
	(C3, C5).								
5.	(C3, C5). Justify the methods used	and obtained results							
5.	,	and obtained results							
	Justify the methods used	and obtained results							
l stu	Justify the methods used (C6).	and obtained results Student learning							
l stu	Justify the methods used (C6). Ident learning time								
l stu	Justify the methods used (C6). Ident learning time	Student learning							
l stu	Justify the methods used (C6). Ident learning time	Student learning							
l stu	Justify the methods used (C6). Ident learning time	Student learning							
l stu	Justify the methods used (C6). Ident learning time	Student learning							
l stu	Justify the methods used (C6). Ident learning time Contact hours	Student learning							
l stu	Justify the methods used (C6). Ident learning time Contact hours	Student learning time (Hrs)							
l stu	Justify the methods used (C6). Ident learning time Contact hours	Student learning time (Hrs)							
l stu	Justify the methods used (C6). Ident learning time Contact hours	Student learning time (Hrs)							
l stu	Justify the methods used (C6). Ident learning time Contact hours	Student learning time (Hrs)							
	5. 6. 1. 2.	 (C3). 5. Prepare and present presentation slides (C3, C). 6. Develop project in hardware/software or both (C5). 1. Prepare the progress report (C3). 3. Prepare and present final slides (C3, C5). 4. Modify and develop 							



Assessment		-		-		
TOTAL		14			-	
Assessment Methods:		•				
Formative:				Summativ	ve:	
Project Problem Selection				Mid-Term	Presentation	
Synopsys review				Second sta	atus review	
First status review				Final Presentation		
Mapping of assessment with	n Cos					
Nature of assessment	CO 1	CO 2	CO 3	CO 4	CO 5	
Mid Presentation	*	*				
Presentation	*	*	*	*	*	
Feedback Process	End-Semes	ster Feedl	oack		1	
Reference Material Particu	ılar to the ch	osen pro	ject			

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

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

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