Course Code	18AIE339T	Course Name	Matrix Theory	r for Artificial Intelligence	Course Category	Ε	Professional Elective	3	T 0	P 0	3
Pre-requisite Courses	Nil		Co-requisite Courses	Nil	Progre		Nil				
Course Offering	g Department	Artificial Intellige	ence	Data Book/Codes/Standards	Nil						

Cours	Course Learning Rationale (CLR): The purpose of learning this course is to:										P	rogra	am Lea	arning	Outc	omes	(PLO)				
Course	Course Objective: The purpose of learning this course is to:						Learning Program Learning Outcomes (PLO)														
1	Understand the basic concep	ts of linear algebra through computer science and Engineering applications		1-6			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	Learn the basic concepts of n	natrix calculus	(L	(9	9																
3	Perform matrix analysis for va	arious optimization algorithms	(Bloom)	y (%)	ıt (%		dge		ent						Work		ance				
4	Apply the concepts of vector spaces, linear transformations, matrices and inner product spaces in engineering				Attainment (%)		Knowledge	S	Development	ί,	Tool Usage	Ф					Finar	ng			
5	Solve problems in computer v	rision using optimization algorithms with single and multi-variables for large datasets	Thinking	Proficiency	tain			Analysis	svelc	sigr	l Us	Culture	∞ >		Team	ion	∞ర	arning			
			불				ring	Ans	& De	, De	20	چ ت	ment			jcal	Mgt.	프			
Course	Outcomes (CO):	At the end of this course, learners will be able to:	Level of	Expected	Expected		Engineering	Problem	esign	Analysis Researc	dem	Society 8	Environr Sustaina	Ethics	Individual &	Communication	Project N	Life Long	PS0 - 1	PS0 - 2	PSO - 3
CO-1:	Solve the basic concepts of li	near algebra through computer science and Engineering applications	3	70	75		3	3	3	-	-	-	-	-	-	-	-	3	-	-	-
CO-2:	Interpret the basic concepts of matrix calculus				75		3	2	2		-	-	-	-	-	-	-	3	-	-	-
CO-3:	Use various matrix analysis methods for solving optimization problems				75		3	2	2	-	-	-	-	-	-	-	-	3	-	-	-
CO-4:	Relate the basic concepts of inner product space, norm, angle, Orthogonality and projection and implementing the Gram-Schmidt process, to obtain least square solution and SV in engineering				75		3	2	2	1	-	-	-	-	-	-	-	3	-	-	-
CO-5:	Interpret the concept of multi-	variable optimization techniques	3	70	75		3	2	2	-	-	-	-	-	-	-	-	3	-	-	-

Duration	(hour)	Linear Systems	Matrix Calculus	Matrix Analysis	Matrix Solutions	Optimization		
S-1	SLO-1	Linear Systems -	MatrixCalculus	Jacobian Matrix	GaussElimination	D : (0 /: /		
5-1	SLO-2	IntroductiontoLinear Algebra	MatrixDecomposition	Jacobian Matrix	Gausseumination	Basics of Optimization		
	SLO-1 LinearAlgebraandAI		Operation and Properties of					
S-2	SLO-2	Examples of Linear AlgebrainAI	Matrix(Identity -Diagonal- Transpose-Symmetric-Trace- Norms)	GradientMatrix	ConjugateGradientMethods	Univariate-Bivariate-Multivariate		
S-3	SLO-1	From Fundamental System Operation and Properties of Matrix(Rank-Inverse- Orthogonal -		RealMatrixDifferential	SingularValueDecomposition	ConvexObjectiveFunctions		
3-3	SLO-2 of Solutions to Liv		Range -Determinant))	кешманхыдегении	Singular value Decomposition	Convexobjectiver unctions		
S4	SLO-1	C	CramersRule	Complete Constitute Matrices	Land Carrama Made a J	Minutine Condition December		
34	SLO-2	SystemofLinear Equations	Cramerskuie	ComplexGradientMatrices	LeastSquareMethod	MinutiaeofGradientDescent		

	SLO-1 Matrices		EigenvaluesandEigenVectors	Gradient of Complex				
S-5	SLO-2	Solving Systems of LinearEquations	CholeskyDecomposition	variablefunction	GradientComputation	OptimizationinAI		
S-6	SLO-1	VastauCu aaaa	OP decomment ion	Gradient Method for smooth	Cuadiout Descending	Ontimi-ationin AI		
3-0	SLO-2	VectorSpaces	QRdecomposition	convexoptimization	GradientDescending	OptimizationinAI		
S-7	SLO-1	Linear Independence -	IIIdaaamaaitian	Gradient Method for smooth	Tibbon on Doon lawin astion	ApplicationsofMatrixinAI		
3-7	SLO-2	BasisandRank	LUdecomposition	convexoptimization	TikhonovRegularization	Аррисанопѕојманхим		
S-8	SLO-1	LinearMapping	Eigen decomposition	Non-smoothconvexoptimization	Gauss-Seidelmethod	ApplicationsofMatrixinAI		
	SLO-2	Linearmapping	andDiagonalization	ivon-smooinconvexopiimizaiion	Gauss-setaetmethoa	Аррисановојманыны		
S-9	SLO-1		SingularvalueDecomposition	ConstrainedConveyOntimization	Application: Gradient Explosion	CasaStudy		
3-9	SLO-2		PCA	- ConstrainedConvexOptimization	andGradientVanishing	CaseStudy		
S-10	SLO-1		MatrixApproximation					
3-10	SLO-2		Matrixcalculus					

Learning
Resources

- 1. Xian-DaZhang,AMatrixAlgebraApproachtoArtificialIntelligence,Springer,2021
- Xian-DaZhang, Matrix Analysis and Applications Cambridge University Press, 2017
 Charu C. Aggarwal, Linear Algebra and Optimization for Machine Learning, Springer, 2020.
- Stephen Boyd, Lieven Van den berghe, Introduction to Applied Linear Algebra-Vectors, Matrices, and Least Squares, Cambridge University Press, 2018 Linear Algebra-Kenneth Hoffman and Ray Kunze, Prentice Hall India, 2013. Linear Algebra-Cheney and Kincaid, Jones and Bartlettlearning, 2014

Learning Ass	essment													
Continuous Learning Assessment (50% weightage)											F: 15 : (500/ : 14)			
	Bloom's Level of Thinking	CLA – 1 (10%)		CLA – 2 (15%)		CLA – S	CLA – 3 (15%)		4 (10%)	Final Examination (50% weight				
	2010.0.1	Theory		Theory	Practice	Theory	Practice	Theory	Practice	Theory	Practice			
Level 1	Remember	20%	-	15%	-	15%	-		-	15%	-			
Level 2	Understand	20%	-	25%	-	25%	-		-	20%	-			
Level 3	Apply	25%	-	35%	-	20%	-	25%	-	35%	-			
Level 4	Analyze	15%	-	15%	-	20%	-	30%	-	20%	-			
Level 5	Evaluate		-		-	10%	-	25%	-		-			
Level 6	Create	20%	-	10%	-	10%	-	20%	-	10%	-			
	Total	100 %	-	100 %	-	100 %	-	100%	-	100%	-			

#CLA-4canbefromanycombinationofthese: Assignments, Seminars, TechTalks, Mini-Projects, Case-Studies, Self-Study, MOOCs, Certifications, Conf. Paperetc.,

Course Designers		
Experts from Industry	Experts from Higher Technical Institutions	Internal Experts
Dr.Marriappan Vaithilingam, Senior Director of Engineering, Freshworks	Dr.Udendran,Dept.ofCSE.,Bharathidasan University,Tiruchirappalli	Mr.C.Arun,Asst Prof, SRM Institute of Science and Technology