

Course Code	PAD21D06T	Course Name	REINFORCEMENT LEARNING FOR AI	Course Category	D	Discipline Specific Elective	L	T	P	C
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Pre-requisite Courses	Artificial Intelligence	Co-requisite Courses	Nil	Progressive Courses	Nil
Course Offering Department	Computer Applications	Data Book / Codes/Standards		Nil	

Course Learning Rationale (CLR):	The purpose of learning this course is to:	Learning	Program Learning Outcomes (PLO)
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CLR-1 :	To understand the concept of algorithms helps approach problems with simple step by step solutions.	1	2	3	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
CLR-2 :	To apply creative thinking towards the problem which would help in having a solution-oriented mindset	Le	Ex	Ex	Dis	Cri	Pr	An	Re	Te	Sci	Re	Sel	Mu	Eth	Co	IC	Le	Lif
CLR-3 :	To develop the students, have familiarity with them and stays relevant to the future modern world	vel	pe	pe	cipl	tical	obl	aly	se	am	ent	fl	f-D	ltic	mu	mun	T	ad	Long
CLR-4 :	To develop the abilities creates new opportunities in most business sectors and consumer applications.	of	ct	ct	inary	al	em	tical	arc	Wo	ific	ctiv	Direct	ult	ical	ity	Ski	ers	Le
CLR-5 :	To develop the decision-making knowledge.	Thi	Pr	Att	Know	Thi	Sol	Re	h	rk	Re	e	ed	ura	Re	En	lls	hip	Long
Course Learning Outcomes (CLO):	At the end of this course, learners will be able to:	ng	of	ain	ledge	ng	ving	ason	ills		ason	Thi	Le	Comp	as	ga		Ski	Le
CLO-1:	Learn how to define RL tasks and the core principals behind the RL, including policies, value functions	(B	ci	me										ete	oni	me			
CLO-2 :	Implement in code common algorithms following code standards and libraries used in RL	loo	nc	nt	3	85	80	M	L	L	-	L	-	M	L	L	L	M	L
CLO-3 :	Understand and work with tabular methods to solve classical control problems	m)	y	(%	3	80	70	-	L	H	-	H	-	H	M	H	M	L	M
CLO-4 :	Explore imitation learning tasks and solutions)	(%)	3	70	65	M	M	H	-	H	-	M	M	H	M	L	M
CLO-5 :	Recognize current advanced techniques and applications in RL				3	70	70	H	H	M	-	M	-	H	L	M	L	M	H
					3	80	70	-	M	M	-	M	-	H	M	H	M	M	H

Duration (hour)	12	12	12	12	12	12
S-1	SLO-1	Reinforcement learning basics	RL formalisms and relations	Open AI Gym	Deep Q-Networks	Learning All possible policies with Entropy Methods
S-2	SLO-1	Use and applications of RL	Rewards in RL	The Random Cartpole agent	Deep Learning Architecture	Maximum Entropy RL
S-3	SLO-1	Reinforcement learning as MDF	Agents in Reinforcement learning	The extra Gym Functionality - Wrapper and monitors	Deep Q-Learning	Soft Actor-Critic
S-4	SLO-1	Learnable Functions in Reinforcement learning	The environnent	Deep Learning with PyTorch	Rainbow DQN	Extension to maximum Entropy Methods

S-5	SLO-1	Reinforcement learning and machine learning	Actions	Tensors	Example: Rainbow DQN on Atari Games	Performance Comparison: SAC Versus PPO
S-6	SLO-1	Taxonomy of RL Approaches	Observations	Gradients	Other DQN Improvements	Industrial Example: Learning to drive with a remote control car
S-7	SLO-1	Reinforcement learning flow	Markov decisions process	NN building blocks	Policy Gradient Methods	Rethinking the MDP
	SLO-2	Deep Reinforcement learning Algorithms	Inventory Control and control simulation	Custom layers	Benefits of Learning a Policy Directly	Hierarchical RL
S-8	SLO-1	On-Policy and Off - Policy Algorithm	Markov reward process	Final glue - loss functions and optimizers	Policy Gradient Theorem	Multi- Agent RL
	SLO-2	The First RL Algorithm	Markov decision process	Monitoring with Tensor Board	n-Step Actor-Critic and Advantage Actor-Critic (A2C)	Expert Guidance
S-9	SLO-1	Compare and contrast RL and ML	Rewards Engineering	GAN on Atari images	Industrial Example: Automatically purchasing products for customers	Other Paradigms
	SLO-2	State change and transition process	Policy Evaluation: The Vale Function	The Cross-Entropy Method	Beyond Policy Gradients	The RL Project Life sysle
S-10	SLO-1	RL as a Discipline	Policy Improvement: Choosing the Best Action	Taxonomy of RL methods	Off-Policy Algorithms	Problem definition in RL
	SLO-2	Deep Learning for Reinforcement learning	Improving the e-greedy Algorithm	Cross entropy on cartpole and Frozem Lake	Deterministic policy Gradients	RL Engineering and refinement
S-11	SLO-1	Reinforcement learning and Supervised Learning	Policies and Value Functions	Theoretical background of the cross-entropy method	Trust Region Methods	Mapping policies and Action spaces
	SLO-2	Lack of an Oracle	Discounted Rewards	Tabulate Learning and the Bellman equation	Using Servos for a Real-Life Reacher	Operational RL Implementation and Deployment
S-12	SLO-1	Sparsity of Feedback	Monte Carlo Policy Generation	Value, state and optimality	Other policy Gradient Algorithms	Conclusion and the future Tips and Tricks
	SLO-2	Data Generation.	Value Iteration with Dynamic Programming	Q-Learning for FrozenLake	Extensions to policy Gradient Algorithms	The future of RL

Learning Resources	<ol style="list-style-type: none"> 1. Deep Reinforcement Learning Hands-On - Second Edition, Maxim Lapan, January 2020 2. Reinforcement Learning, By Phil Winder, March 2020 3. Foundations of Deep Reinforcement Learning: Theory and Practice in Python, By Laura Graesser and Wah Loon Keng, December 2019.
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Learning Assessment											
Level	Bloom's Level of Thinking	Continuous Learning Assessment (50% weightage)								Final Examination (50% weightage)	
		CLA – 1 (10%)		CLA – 2 (10%)		CLA – 3 (20%)		CLA – 4 (10%) #			
		Theory	Practice	Theory	Practice	Theory	Practice	Theory	Practice	Theory	Practice
Level 1	Remember	30%	-	30%	-	30%	-	30%	-	30%	-
	Understand										
Level 2	Apply	40%	-	40%	-	40%	-	40%	-	40%	-
	Analyze										
Level 3	Evaluate	30%	-	30%	-	30%	-	30%	-	30%	-
	Create										
	Total	100 %		100 %		100 %		100 %		100 %	

CLA – 4 can be from any combination of these: Assignments, Seminars, Short Talks, Mini-Projects, Case-Studies, Self-Study, MOOCs, Certifications, Conf. Paper etc.,

Course Designers		
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