Course Code:	Course Title	Credit
ADDOL8013	**Reinforcement Learning Lab**	**1**

Prerequisite: Python Programming, Deep Learning, Machine Learning.

Lab Objectives: Students will try

1	Introduce the fundamentals of reinforcement learning and problem formulation using MDPs and Bandit problems
2	Explode different exploration strategies and their impact on online leaning scenarios.
3	Understand dynamic programming algorithms for solving Markov Decision Processes.
4	Apply dynamic programming techniques to solve small-scale MDP problems
5	Implement and compare Monte Carlo methods and Temporal-Difference learning algorithms.
6	Explore real-world applications of reinforcement learning in domains such as autonomous driving or robotics

Lab Outcomes: At the end of the course, the students will be able to

1	Gain a solid understanding of reinforcement learning concepts and problem formulation.
2	Evaluate and compare exploration strategies in online learning scenarios.
3	Solve Markov Decision Processes using dynamic programming algorithms
4	Apply dynamic programming techniques to solve small-scale MDP problems.
5	Implement and analyze Monte Carlo methods and Temporal-Difference learning algorithms
6	Explore practical applications of reinforcement learning in real-world domains.

Sr. No.	Suggested List of Experiments
1.	Implementing a simple grid-world environment and training an agent using basic Q-learning
2.	Implementing a multi-armed bandit problem and comparing different exploration strategies like epsilon-greedy and UCB.
3,	Implementing a basic grid-world environment as an MDP and applying policy iteration and value iteration algorithms to find optimal policies.
4.	Applying dynamic programming algorithms, such as policy evaluation and policy improvement, to solve a small-scale MDP problem.
5.	Implementing Monte Carlo control and Temporal Difference (TD) learning algorithms to train an agent in a grid-world environment.
6.	Exploration vs. Exploitation Trade-off: Experimenting with different exploration strategies and analyzing their impact on the learning performance of an agent in a bandit problem.
7.	Function Approximation in Reinforcement Learning: Using function approximation techniques, such as linear regression or neural networks, to approximate value functions in reinforcement learning problems.

8.	Deep Reinforcement Learning: Implementing a deep Q-network (DQN) to train an agent to play a popular Atari game, such as Pong or Space Invaders.
9.	Transfer Learning and Multi-Task Reinforcement Learning: Investigating transfer learning in reinforcement learning by training an agent in one environment and transferring its knowledge to a different but related environment
10.	Policy Gradient Methods: Implementing policy gradient methods, such as REINFORCE or Proximal Policy Optimization (PPO), to train an agent in a continuous control environment.
*11.	Applications and Case Studies: Applying reinforcement learning techniques to solve a real-world problem, such as training a self-driving car to navigate a simulated road environment.

Textbooks	
1	Reinforcement Learning: An Introduction, by Richard S. Sutton and Andrew G. Barto
2	Alessandro Palmas, Dr. Alexandra Galina Petre, Emanuele Ghelfi, The Reinforcement Learning Workshop: Learn how to Apply Cutting-edge Reinforcement Learning Algorithms to a Wide Range of Control Problems, 2020 Packt publishing.
3	Phil Winder, Reinforcement Learning Industrial Applications with Intelligent Agents, O'Reilly
4	Dr Engr S M Farrukh Akhtar, Practical Reinforcement Learning, Packt Publishing, 2017.
References Books	
1	Maxim Lapan, Deep Reinforcement Learning Hands-On: Apply modern RL methods, with deep Q-networks, value iteration, policy gradients, TRPO, AlphaGo Zero.
2	Csaba Szepesv´ari, Algorithms for Reinforcement Learning, Morgan & Claypool Publishers
3	Alberto Leon-Garcia, Probability, Statistics and Random Processes for Electrical Engineering, Third Edition, Pearson Education, Inc.

Useful Links	
1	Machine Learning and Friends at Carnegie Mellon University
2	Reinforcement Learning: A Survey
3	Bibliography on Reinforcement Learning
4	David J. Finton's Reinforcement Learning Page

Term Work:	
1	Term work should consist of 8(min) to 12(max) experiments.
2	The final certification and acceptance of term work ensures satisfactory performance of laboratory work and minimum passing marks in term work.
3	Total 25 Marks for Experiments
Evaluation Exam	
Based on the subject and related lab of **Reinforcement Learning and theory**	