

Binarath NSTITUTE OF HIGHER EDUCATION AND RESEARCH

BHARATH INSTITUTE OF SCIENCE AND TECHNOLOG No.173, Agharam Road, Selaiyur, Chennai, T.N. - 600 073.

Requisition Letter

Date: 03.01.2019

From Dr. K.P Kaliyamurthie Professor & Head, Department of CSE, Bharath Institute of Higher Education and Research, Chennai

To The Dean Engineering, Bharath Institute of Higher Education and Research, Chennai

Respected sir,

Subject : Request of Permission to conduct a value added course on "**Reinforcement Learning**" -Reg

With reference to above subject, I would like to bring to your kind notice that, our department interested to organize value added course on "**Reinforcement Learning**" in our campus premises from 30.01.2019 for 38hours

Ourinternal Professorswould deliver lecture for the above mentioned course. About 50 students would be participating in this course. We request you kindly to give permission to organize this.

Venue: CSEClass room

Timing: 1:30 PM to 4:30 PM Friday (AN) and

9.00 PM to 4.00 PM Saturday (FN&AN).

Submitted to Principal for approval to organize this value added course.

HOD/CSE

DEAN ENGINEERING

HEAD OF DEPARTMENT partment of Computer Sole & Engg., aruth Institute of Higher Education & Research eclared as Deemed to be University U.S.3 of UGC Act, 1956) Chennai-600 073. INDIA



CIRCULAR

25.01.2019

The School of computing, Bharath Institute of Higher Education and Research is planned to conduct a certification value added course on **Reinforcement Learning**for the benefit of II, III and IV year students. This course is scheduled from 30.01.2019 for 38hours which includes theory and practical. The timings are 1:30 PM to 4:30 PM from Friday (AN) and Saturday (FN&AN).

All Registered Students must attend all the classes without fail. The following faculty members are assigned to handle the course. S.NO	Name of the Faculty	Designation
1	Dr.K.P.Kaliyamurthie	Professor
2	Dr.C.Rajabhushanam	Professor

Head of Department

HEAD OF DEPARTMENT Department of Computer Scie A Engg., Bharath Institute of Matter Education Sciences Declared as Control and Sciences (6)

То

Copy to CSE

Copy to IT



CERTIFICATE COURSE ON REINFORCEMENT LEARNING Date of Introduction of the Course: 30.01.2019

COURSE OBJECTIVE

Reinforcement Learning is a subfield of Machine Learning, but is also a general purpose formalism for automated decision-making and AI. This course introduces you to statistical learning techniques where an agent explicitly takes actions and interacts with the world. Understanding the importance and challenges of learning agents that make decisions is of vital importance today, with more and more companies interested in interactive agents and intelligent decision-making. This course introduces you to the fundamentals of Reinforcement Learning.

WHAT TO EXPECT

- ✓ Formalize problems as Markov Decision Processes
- Understand basic exploration methods and the exploration/exploitation tradeoff
- ✓ Understand value functions, as a general-purpose tool for optimal decision-making
- ✓ Know how to implement dynamic programming as an efficient solution approach to an industrial control problem

COURSE SYLLABUS

1. Introduction to RL and immediate RL

- Introduction to RL
- RL Framework and applications
- Introduction to immediate RL
- Bandit optimalities
- Value function based methods

2. Bandit algorithm

- UCB 1
- Concentration bounds
- UCB 1 theorem
- PAC bounds
- median elimination
- Thompson sampling

3. Policy gradient methods and introduction to full reinforcement learning

- Policy search
- Reinforce
- Contextual bandits
- Full reinforcement learning introduction
- Returns, value functions and MDP

4. MDP formulation, bellman equations and optimality proof

- MDP modelling
- Bellman equations
- Bellman optimality equation
- Cauchy sequence and green's equation
- Banach fixed point theorem
- Convergence proof

5. Dynamic programming and Monte Carlo methods

- Lpi convergence
- Value iteration
- Policy iteration
- Dynamic programming
- Montu kar lo
- Control in Monte Carlo

6. Monte Carlo and temporal difference methods .

- Off policy MC
- UCT
- TD(0)
- TD(0) control
- Q learning
- After state

7. Eligibility traces

- eligibility traces
- Backward view of eligibility traces
- Eligibility trace control
- Thompson sampling recap

8. Function approximation

- Function approximation
- Linear parametrization
- State aggregation methods
- Function of approximation and eligibility traces
- LSTD & LSTDQ
- LSPI & fitted Q

9. DQN, Fitted Q & policy gradient approaches

- DQN and fitted Q Iteration
- Policy gradient approach
- Actor critic and reinforce
- Policy Gradient with function approximation

10. Hierarchical reinforcement learning

- Hierarchical Enforcement learning
- Types of optimality
- Semi Markov decision processes
- Options
- Learning with options
- Hierarchical abstract machines.

11. Hierarchical reinforcement learning - MAXQ

- MAXQ
- MAXQ value function decomposition
- Option Discovery

12. POMDP

- POMDP introduction
- Solving POMDP

COURSE COORDINATOR

HEAD OF THE DEPARTMENT

HEAD OF DEPARTMENT Department of Computer Scic & & Engg., Bhurath Institute of Higher Education & Research (Declared as Deemed to be University U/S 3 of UGC Act, 1956) Chennal-600 073. INDIA



CERTIFICATE COURSE ON REINFORCEMENT LEARNING Date of Course Introduction 30/01/2019

School Of Computing

Registered Students List

S.NO	REG.NO	NAME OF THE STUDENT
1	U15CS001	ABHIJEET KUMAR
2	U15CS002	ABHIJIT KUMAR GUPTA
3	U15CS003	ABHISHEK KUMAR SINGH
4	U15CS004	ALLU SAI SIVA PRIYANKA NAIDU
5	U15CS005	AMBIKE KUMAR SINGH
6	U15CS006	ANBUMANI S
7	U15CS007	ANJAR ALI
8	U15CS008	ANKAM MANJUNATH
9	U15CS009	ANNADI DHANUSH
10	U15CS011	ANUMOLU YESWANTH
11	U15CS012	ARAVAPALLI SIVA VINAYA
12	U15CS013	ARAVINDHAN K R
13	U15CS014	ARVIND KUMR YADAV
14	U15CS015	ARYAN SAHU
15	U15CS016	ASHISH AGARWAL
16	U15CS064	INJE RAVI TEJA
17	U15CS065	INNURU SWATHI
18	U15CS066	JAGADEESH K
19	U15CS067	JAGADEESWARA RAO JADDU
20	U15CS068	JAICHAND KUMAR
21	U15CS069	JANAKI RAMAN V
22	U15CS071	JOHN PARAM JYOTHI JYOTHULA
23	U15CS073	K THULASIRAM
24	U15CS074	KADALI VINAYNARASIMHA
25	U15CS075	KADUMU MOUNIKA
26	U15CS076	KAIPU PRANAY REDDY
27	U15CS077	KALYANAM JASWANTH NAIDU
28	U15CS078	KAMBLE NIKHIL KUMAR
29	U15CS079	KANCHARLAPALLI LOKESHWAR RAO
30	U15CS080	KANCHUMARTHI BHUVANESWAR VINAY
31	U15CS127	MUPPALLA SURENDRA
32	U15CS128	MURARI KUMAR CHAUDHARY
33	U15CS129	N SWAPNA RAAGA
34	U15CS130	NAGANNAGARI JAGADISH
35	U15CS133	NALLURI AKHIL BABU
36	U15CS134	NAMBURI VIJAY KUMAR

	111500125	NARENDULA NIREESHA
37	U15CS135	
38	U15CS136	NARESH K
39	U15CS138	NEELA SAI KUMAR
40	U15CS139	NIKHIL KUMAR
41	U15CS140	NIRANJAN S
42	U15CS141	NITIN SINGH
43	U15CS142	NUKALA BHODANANDA CHARAN
44	U15CS143	OLIVER S
45	U15CS144	OMPRAKASH YADAV
46	U15CS191	SEETAPTI HEMA SEKHAR
47	U15CS192	SESHA SRUJAN.B
48	U15CS193	SHAIK AFRIDI
49	U15CS194	SHAIK SABIR
50	U15CS195	SHAIK YASMEEN
K	e Coordinator	1 KIN

HEAD OF DEPARTMENT Department of Computer Scie & Engg., Bharath Institute of Higher Education & Research (Declared as Deemed to be University U/S 3 of UGC Act, 1956) Chennai-600 073. INDIA



CERTIFICATE COURSE ON REINFORCEMENT LEARNING

Date of Introduction of the Course: 31.01.2019

The timings are 1:30 PM to 4:30 PM from Friday (AN) and Saturday (FN&AN)

CLASS	DATE	TOPIC
1,2	30-01-2019	Introduction to RL
-,-		RL Framework and applications
3,4,	02-02-2019	Introduction to immediate RL
3,4,		Bandit optimalities
5,6		Value function based methods
		• UCB 1
		Concentration bounds
		• UCB 1 theorem
7.0	08-02-2019	PAC bounds
7,8	08-02-2019	median elimination
		Thompson sampling
0.10	00.02.2010	Policy search
9,10,	09-02-2019	Reinforce
11,12		Contextual bandits
		• Full reinforcement learning introduction
		• Returns, value functions and MDP
13,14	15-02-2019	MDP modelling
13,14	15-02-2019	Bellman equations
		Bellman optimality equation
		Cauchy sequence and green's equation

Time Table& Lesson plan

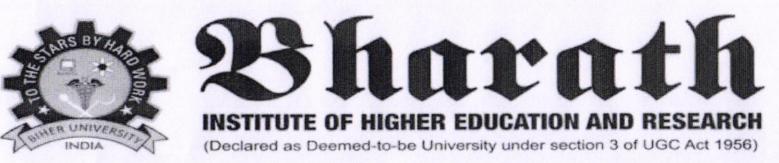
15,16,16.0-2-00917,18- Convergence proof17,18- Die convergence19,2022-02-201919,2022-02-201921,22,23-02-201921,22,23-02-201921,22,23-02-201923,24- UCT21,22,23-02-201923,24- UCT21,22,23-02-201923,24- UCT21,22,23-02-201923,24- UCT21,22,23-02-201923,24- Eligibility traces25,2601-03-201901-03-2019- Eligibility traces25,2601-03-201927,28,02-03-201927,28,02-03-201927,28,02-03-201931,3208-03-201931,3208-03-201931,3209-03-201933,34,35,3609-03-201933,34,35,3609-03-201931,3209-03-201931,3209-03-201931,3209-03-201931,3209-03-201931,34- Hierarchical Enforcement learning- Types of optimality- Semi Markov decision processes- Options- Control- Control			Banach fixed point theorem
17,18. Lpi convergence90icy iterationPolicy iteration19,2022-02-2019. Dynamic programming19,2022-02-2019. Montu kar lo21,22,23-02-2019. UCT21,22,23-02-2019. UCT23,24. UCT. TD(0)23,24. UCT. TD(0)25,2601-03-2019. eligibility traces25,2601-03-2019. Eligibility traces27,28,02-03-2019. Function approximation27,28,02-03-2019. Function approximation21,3208-03-2019. Eligibility trace control31,3208-03-2019. DQN and fitted Q Iteration31,3209-03-2019. DQN and fitted Q Iteration33,34,35,3609-03-2019. Hierarchical Enforcement learning33,34,35,3609-03-2019. Hierarchical Enforcement learning31,3209-03-2019. Hierarchical Enforcement learning33,34,35,36. Dynamic proses. Options31,31. Dynamic proses. Options33,34,35,36. Dynamic proses. Options31,32. Dynamic proses. Options33,34,35,36. Dynamic proses. Options31,32. Dynamic proses. Options33,34,35,36. Dynamic proses. Options31,32. Dynamic proses. Options31,34. Dynamic proses. Options31,35. Dynamic proses. Options31,35. Dynamic proses. Options31,35.	15,16,	16-02-2019	
Policy iteration19,2022-02-201922-02-2019• Dynamic programming • Montu kar lo • Control in Monte Carlo • Off policy MC21,22, 23,2423-02-201921,22, 23,2423-02-201921,22, 23,2423-02-201921,22, 23,2423-02-201921,22, 23,2423-02-201921,22, 23,2423-02-201921,22, 23,2423-02-201921,22, 23,2401-03-201925,2601-03-201925,2601-03-201927,28, 29,3002-03-201927,28, 29,3002-03-201921,3202-03-201931,3208-03-201931,3208-03-201931,3208-03-201931,3209-03-201931,34,35,3609-03-201933,34,35,3609-03-20199-03-2019• Hierarchical Enforcement learning • Types of optimality • Semi Markov decision processes • Options • Learning with options	17,18		
19,2022-02-2019• Policy iteration19,2022-02-2019• Montu kar lo19,2022-02-2019• Montu kar lo21,22, 23,2423-02-2019• UCT21,22, 23,2423-02-2019• UCT23,24• D1-03-2019• Eligibility traces25,2601-03-2019• eligibility traces27,28, 29,3002-03-2019• Function approximation27,28, 31,3202-03-2019• Function approximation31,3208-03-2019• DQN and fitted Q Iteration33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Hierarchical Enforcement learning31,3209-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Larning with options			
19,2022-02-2019• Dynamic programming • Montu kar lo • Control in Monte Carlo • Off policy MC21,22, 23,2423-02-2019• UCT • TD(0) • TD(0) control • Q learning • After state25,2601-03-2019• eligibility traces • Eligibility traces • Eligibility trace control • Thompson sampling recap27,28, 29,3002-03-2019 • Function approximation • Linear parametrization • State aggregation methods • Function of approximation and eligibility traces • LSPI & fitted Q • DQN and fitted Q Iteration • Actor critic and reinforce • Policy gradient approach • Actor critic and reinforce • Policy Gradient with function approximation • Hierarchical Enforcement learning • Types of optimality • Semi Markov decision processes • Options • Learning with options			
19,2022-02-2019. Montu kar lo21,22, 23,2423-02-2019. UCT21,22, 23,2423-02-2019. UCT23,24. UCT. TD(0)23,24. After state25,2601-03-2019. eligibility traces27,28, 29,3002-03-2019. Function approximation27,28, 29,3002-03-2019. Function approximation31,3208-03-2019. DQN and fitted Q31,3208-03-2019. DQN and fitted Q lteration33,34,35,3609-03-2019. Hierarchical Enforcement learning33,34,35,3609-03-2019. Hierarchical Enforcement learning. Types of optimality . Semi Markov decision processes . Options . Learning with options. Hierarchical Enforcement learning			
 Control in Monte Carlo Off policy MC UCT TD(0) 23,24 UCT TD(0) control Q learning After state 25,26 01-03-2019 eligibility traces Eligibility trace control Eligibility trace control Thompson sampling recap 27,28, 02-03-2019 Function approximation Linear parametrization State aggregation methods Function of approximation and eligibility traces LSTD & LSTD Q State aggregation methods Policy gradient approach Actor critic and reinforce Policy Gradient with function approximation 33,34,35,36 09-03-2019 Hierarchical Enforcement learning Types of optimality Semi Markov decision processes Options Learning with options 	19,20	22-02-2019	
21,22, 23,2423-02-2019• UCT21,22, 23,24• UCT• TD(0)23,24• TD(0) control• Q learning• After state• eligibility traces25,2601-03-2019• eligibility traces25,2601-03-2019• eligibility traces27,28, 29,3002-03-2019• Function approximation27,28, 29,3002-03-2019• Function approximation21,3208-03-2019• Function of approximation and eligibility traces31,3208-03-2019• DQN and fitted Q Iteration33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Larning with options			
21,22, 23,2423-02-2019• UCT • TD(0) • TD(0) control • Q learning • After state25,2601-03-2019• eligibility traces • Backward view of eligibility traces • Eligibility trace control • Thompson sampling recap27,28, 29,3002-03-2019• Function approximation • Linear parametrization • State aggregation methods • Function of approximation and eligibility traces • LSPI & fitted Q31,3208-03-2019• DQN and fitted Q Iteration • Policy gradient approach • Actor critic and reinforce • Policy Gradient with function approximation33,34,35,3609-03-2019• Hierarchical Enforcement learning • Types of optimality • Semi Markov decision processes • Options • Learning with options			
21,22, 23,2423-02-2019• TD(0)23,24• TD(0) controlQ learning• After state25,2601-03-2019• eligibility traces25,2601-03-2019• eligibility traces27,28, 29,3002-03-2019• Function approximation27,28, 29,3002-03-2019• Function approximation31,3208-03-2019• DQN and fitted Q Iteration31,3208-03-2019• DQN and fitted Q Iteration33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Linear paramity33,34,35,3609-03-2019• Learning with options			
23,24 23,24 - TD(0) control - Q learning - After state - eligibility traces - eligibility traces - Eligibility trace control - Thompson sampling recap - Function approximation - Linear parametrization - State aggregation methods - Function of approximation and eligibility traces - LSTD & LSTDQ - LSPI & fitted Q - State approach - Actor critic and reinforce - Policy gradient approach - Actor critic and reinforce - Policy Gradient with function approximation - Hierarchical Enforcement learning - Types of optimality - Semi Markov decision processes - Options - Learning with options - Tompson sampling recap - Policy Gradient with options - Types of optimality - Semi Markov decision processes - Options - Learning with options - Tompson sampling recap - Tompson sampling recap - Policy Gradient with options - Coptions - Carring with options - Coptions - Coptions	21.22.	23-02-2019	
25,2601-03-2019• Q learning • After state25,2601-03-2019• eligibility traces • Eligibility trace control • Thompson sampling recap27,28, 29,3002-03-2019 • Function approximation • Linear parametrization • State aggregation methods • Function of approximation and eligibility traces • Eligibility traces31,3208-03-2019 • Policy gradient approach • Actor critic and reinforce • Policy Gradient with function approximation33,34,35,3609-03-2019 • Function eligibility traces • LSPI & fitted Q • Policy Gradient with function approximation • Policy Gradient with function approximation33,34,35,3609-03-2019 • Types of optimality • Semi Markov decision processes • Options • Learning with options			• TD(0)
25,2601-03-2019• After state25,2601-03-2019• eligibility traces25,2601-03-2019• Backward view of eligibility traces27,28,02-03-2019• Function approximation27,28,02-03-2019• Function approximation29,30• Function of approximation31,3208-03-2019• DQN and fitted Q Iteration31,3208-03-2019• DQN and fitted Q Iteration33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Learning with options	23,24		• TD(0) control
25,2601-03-2019• eligibility traces25,2601-03-2019• eligibility tracesBackward view of eligibility traces• Eligibility trace control27,28,02-03-2019• Function approximation29,30• Function approximation29,30• State aggregation methods100• Function of approximation and eligibility traces21,3208-03-2019• DQN and fitted Q31,3208-03-2019• DQN and fitted Q Iteration33,34,35,3609-03-2019• Hierarchical Enforcement learning33,34,35,3609-03-2019• Hierarchical Enforcement learning• Coptions• Options• Coptions• Coptions• Coptions• Coptions			• Q learning
25,2601-03-2019. Backward view of eligibility traces26,2601-03-2019. Eligibility trace control27,28, 29,3002-03-2019. Function approximation27,28, 29,3002-03-2019. Function approximation29,30. Eligibility trace aggregation methods29,30. State aggregation methods29,30. State aggregation methods31,3208-03-2019. DQN and fitted Q Iteration31,3208-03-2019. DQN and fitted Q Iteration33,34,35,3609-03-2019. Hierarchical Enforcement learning33,34,35,3609-03-2019. Hierarchical Enforcement learning33,34,35,3609-03-2019. Learning with options			After state
 Backward view of eligibility traces Eligibility trace control Thompson sampling recap Function approximation Linear parametrization State aggregation methods Function of approximation and eligibility traces LSTD & LSTDQ LSPI & fitted Q LSPI & fitted Q DQN and fitted Q Iteration Actor critic and reinforce Policy gradient approach Actor critic and reinforce Policy Gradient with function approximation Types of optimality Semi Markov decision processes Options Learning with options 	25.26	01_03_2019	eligibility traces
27,28, 29,3002-03-2019Function approximation29,30- Function approximation29,30- State aggregation methods29,30- State aggregation methods29,30- Function of approximation and eligibility traces29,30- State aggregation methods31,3208-03-201931,3208-03-201933,34,35,3609-03-201933,34,35,3609-03-2019- Hierarchical Enforcement learning- Types of optimality- Semi Markov decision processes- Options- Options <td>23,20</td> <td>01-05-2017</td> <td>Backward view of eligibility traces</td>	23,20	01-05-2017	Backward view of eligibility traces
27,28, 29,3002-03-2019• Function approximation • Linear parametrization • State aggregation methods • Function of approximation and eligibility traces • LSTD & LSTDQ • LSPI & fitted Q31,3208-03-2019• DQN and fitted Q Iteration • Policy gradient approach • Actor critic and reinforce • Policy Gradient with function approximation33,34,35,3609-03-2019• Hierarchical Enforcement learning • Types of optimality • Semi Markov decision processes • Options • Learning with options			Eligibility trace control
27,28, 29,3002-03-2019. Linear parametrization29,30. State aggregation methods9,30. State aggregation methods. Function of approximation and eligibility traces. LSTD & LSTDQ. LSPI & fitted Q. LSPI & fitted Q. DQN and fitted Q Iteration. Policy gradient approach. Actor critic and reinforce. Policy Gradient with function approximation. Hierarchical Enforcement learning. Types of optimality. Semi Markov decision processes. Options. Learning with options			Thompson sampling recap
 2.1,20, 29,30 Elinear parametrization State aggregation methods Function of approximation and eligibility traces LSTD & LSTDQ LSPI & fitted Q LSPI & fitted Q DQN and fitted Q Iteration Policy gradient approach Actor critic and reinforce Policy Gradient with function approximation Hierarchical Enforcement learning Types of optimality Semi Markov decision processes Options Learning with options 	27.20	02 02 2010	Function approximation
31,3208-03-2019• Function of approximation and eligibility traces • LSTD & LSTDQ • LSPI & fitted Q31,3208-03-2019• DQN and fitted Q Iteration • Policy gradient approach • Actor critic and reinforce • Policy Gradient with function approximation33,34,35,3609-03-2019• Hierarchical Enforcement learning • Types of optimality • Semi Markov decision processes • Options • Learning with options	27,28,	02-03-2019	Linear parametrization
31,3208-03-2019• LSTD & LSTDQ • LSPI & fitted Q31,3208-03-2019• DQN and fitted Q Iteration • Policy gradient approach • Actor critic and reinforce • Policy Gradient with function approximation33,34,35,3609-03-2019• Hierarchical Enforcement learning • Types of optimality • Semi Markov decision processes • Options • Learning with options	29,30		State aggregation methods
31,3208-03-2019• DQN and fitted Q Iteration31,3208-03-2019• DQN and fitted Q IterationPolicy gradient approach• Actor critic and reinforcePolicy Gradient with function approximation• Policy Gradient with function approximation33,34,35,3609-03-2019• Hierarchical Enforcement learningTypes of optimality• Semi Markov decision processesOptions• Learning with options			• Function of approximation and eligibility traces
31,3208-03-2019• DQN and fitted Q Iteration990icy gradient approach• Actor critic and reinforce• Policy Gradient with function approximation33,34,35,3609-03-2019• Hierarchical Enforcement learning• Types of optimality• Semi Markov decision processes• Options• Learning with options			LSTD & LSTDQ
31,3208-03-2019Policy gradient approachActor critic and reinforceActor critic and reinforcePolicy Gradient with function approximationPolicy Gradient with function approximation33,34,35,3609-03-2019• Hierarchical Enforcement learningTypes of optimalitySemi Markov decision processesOptions• Learning with options			• LSPI & fitted Q
 Policy gradient approach Actor critic and reinforce Policy Gradient with function approximation Hierarchical Enforcement learning Types of optimality Semi Markov decision processes Options Learning with options 		00.02.0010	DQN and fitted Q Iteration
33,34,35,3609-03-2019• Policy Gradient with function approximation33,34,35,3609-03-2019• Hierarchical Enforcement learning• Types of optimality• Semi Markov decision processes• Options• Options• Learning with options• Learning with options	31,32	08-03-2019	Policy gradient approach
33,34,35,3609-03-2019• Hierarchical Enforcement learning • Types of optimality • Semi Markov decision processes • Options • Learning with options			Actor critic and reinforce
33,34,35,3609-03-2019• Hierarchical Enforcement learning • Types of optimality • Semi Markov decision processes • Options • Learning with options			Policy Gradient with function approximation
 33,34,35,36 09-03-2019 Types of optimality Semi Markov decision processes Options Learning with options 			
 Semi Markov decision processes Options Learning with options 	33,34,35,36	09-03-2019	
OptionsLearning with options			
Learning with options			
			 Hierarchical abstract machines.

17 10	15 03 2010	• MAXQ
37,38	15-03-2019	MAXQ value function decomposition
		Option Discovery
		POMDP introduction
		Solving POMDP

COURSE COORDINATOR

HEAD OF THE DEPARTMENT

HEAD OF DEPARTMENT Department of Computer Science & Engg., Bharath Institute of Higher Education & Research (Declared as Deemed to be University U/S 3 of UGC Act, 1956) Chennai-600 073. INDIA

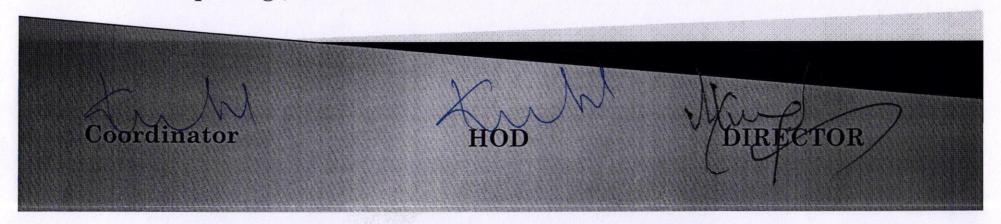


CERTIFICATE OF PARTICIPATION

This is Presented to

Mr. ABHIJEET KUMAR

For actively participating in value added course on "Reinforcement Learning" conducted by School Computing, BIHER from 30-01-2019 to 15-03-2019.



COURSE FEEDBACK FORM

Acade	emic Year		201	9-21	0				
Term									
Cours	e Number		-						
Cours	e Title		Reir	o forc	emont	lenning			
Numb	per of Credits		-						
Туре	of Course	Regular		Elec	ctive	Add-o	on 🔨		
	0								
I.	Informat	ion on the Responde	ent: (Tick ((√) Appr	opriately)				
1.	Percenta	ge of classes attende	d						
1.	0-20	20-40		4	0-60	60-80	-80-		
	0-20	2040				00.00	100		
2.	Number	of hours per week s	pent on the	e course	Other than le	ecture hours)			
	0-2	2-4		4	-6	6-8	8-10		
3.	Preparat	tion for the course b	y the stude	ent:					
	(i)	Have done part of				NO			
	(ii)	Has adequate prior	exposure t	to the pre	requisites	NЬ			
	(iii)	Had to pickup relevant additional topics through concurrent study							
	(iv)	Have no exposure	to the back	ground n	naterial	NO			
4.	The expe	The expectations for taking the course by the student are:							
	(a)	Enhance by skill base in the area of specializations $4eS$							
	(b)	Get exposed to a relevant subject Yes							
	(c)	Curiosity							
	(d)	Better Employment Opportunity							
	(e)	Complete Course	requiremen	requirements X CS					
	(f)	To Improve CGPA				YRS			
Abou	at the Instruc	ctor: Information on	the Respo	ondent: (Гick (√) Appr				
				A	В	С	D	E	
1.	Pace of t	he Teaching/lecture		V					
2.	Commen	Comment of the Subject							
3.	3. Clarity of expression								
4.		preparation							
5.	Level of	interaction		~					
6.		ility outside the class		~					
7.	Others (p	please specify							
		D. V.	land	Kc.	1	D:	E	.	
A: E	xcellent	B: Very G	000 1	C:		D: Satisfactory		oor	
				Good		Satistactory		OUF	

HEAD OF THE DEPARTMENT



CERTIFICATE COURSE ON REINFORCEMENT LEARNING

Date of Course Introduction 30/01/2019 School of Computing



COURSE COORDINATOR

HEAD OF THE DEPARTMENT

Department of Computer Science & Engg., Bharath Institute of Higher Education & Research (Declared as Deemed to be University U/S 3 of UCC Act, 1956) Chennal-600 073, INDIA

COURSE FEEDBACK FORM

cac	lemic Yea	r		2018-	2019						
erm	1	1. N. J. S.									
Cour	se Numbe	er						-			
Cour	se Title		Ro	Entonio	ment	har	940.000	,			
Num	ber of Cro	edits	10	Спрони	reale	All	our rig				
Туре	of Cours	e Regular		Elective		Ad	d-on	1			
Ι.	Inform	ation on the Res	pondent: (Tick	(√) Appropriat	ely)						
1.	Percen	tage of classes a	ttended								
	0-20		20-40	40-6	50	60-80	1 80	-100			
	0.20		20 10								
2.	Numbe	er of hours per w	veek spent on the	e course (Other	than lecture h	iours)					
	0-2		2-4	4-6	1	6-8	8	-10			
2	Dropor	nation for the con	wee by the stud	anti							
3.	(i)		of this course ea				10				
						14	0				
		(ii) Has adequate prior exposure to the prerequisites									
	(iii)	(iii) Had to pickup relevant additional topics through concurrent study 1.2.8 (iv) Have no exposure to the background material 1.2.9									
		nave no expos					7.88				
4.	The ex	pectations for ta	king the course	by the student	are:						
	(a) Enhance by skill base in the area of specializations										
	(b)	(b) Get exposed to a relevant subject 7.9 g									
	(c)	(c) Curiosity									
	(d)	Better Employ	ment Opportunity	y		/	yes				
	(e)	Complete Cour	rse requirements				res				
	(f) To Improve CGPA Yes										
Abo	ut the In	structor: Inform	ation on the Re	spondent: (Ticl							
				A	В	С	D	E			
1.		f the Teaching/lea			1						
2.		ent of the Subjec	t		1						
3.		of expression	Start Land		1						
4.		of preparation			1						
5.		of interaction		1							
6.		ibility outside the	e class	/							
7.	Others	(please specify									
			Very Good	C: Good	1 1.	D: Satisfactor		E: Poor			

HEAD OF DEPARTMENT Department of Computer Scie & Engg., Bharath Institute of Higher Education & Research (Declared as Deemod to be University 0/5/3 of 000 Act, 1956) Chennel-600 073. INDIA