Sri Indu
College of Engineering & Technology
UGC Autonomous Institution
Recognized under 2(f) & 12(B) of UGC Act 1956,
NAAC, Approved by AICTE &
Permanently Affiliated to JNTUH
Estd.2001

NAAC
NATIONAL ASSESSMENT AND ACCREDITATION COUNCIL

# HANDOUT

## III-AIDS-II Semester

## DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

**ACADEMIC YEAR 2024-25**

DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

# HANDOUT-INDEX

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# SRI INDU COLLEGE OF ENGINEERING&TECHNOLOGY

## B.TECH -ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

### VISION OF THE INSTITUTE

To be a premier Institution in Engineering &Technology and Management with competency, values and social consciousness.

### MISSION OF THE INSTITUTE

**$IM_1$** Provide high quality academic programs, training activities and research facilities.

**$IM_2$** Promote Continuous Industry-Institute interaction for employability, Entrepreneurship, leadership and research aptitude among stakeholders.

**$IM_3$** Contribute to the economical and technological development of the region, state and nation.

### VISION OF THE DEPARTMENT

To be a technologically adaptive centre for computing by grooming the students as top notch professionals**.**

### MISSION OF THE DEPARTMENT

**DM1**: To offer quality education in computing.

**DM2**: To provide an environment that enables over all development to fall the stakeholders.

**DM3:** To impart training on emerging technologies.

**DM4**: To encourage participation of stakeholders in research and development.

### PROGRAM EDUCATIONAL OBJECTIVES(PEOs)

**PEO1: Higher Studies:** Graduate with an ability to pursue higher studies and get employment in reputed institutions and organizations.

**PEO2: Domain Knowledge: Graduate** with an ability to design and develop a product.

**PEO3: Professional Career:** Graduate with excellence by multidisciplinary approach to achieve successful professional career.

**PEO4: Life Long Learning: Graduate** with an ability to learn advanced skills to face professional competence through lifelong learning.

**PROGRAM OUTCOMES(POs)&PROGRAM SPECIFIC OUTCOMES(PSOs)**

| POs | Description |
|---|---|
| **PO1** | **Engineering Knowledge:** Apply the knowledge of mathematics,science,engineering Fundamentals, and an engineering specialization to the solution of complex engineering problems. |
| **PO2** | **Problem Analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences. |
| **PO3** | **Design/Development of Solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural,societal,and environmental Considerations. |
| **PO4** | **Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions. |
| **PO5** | **Modern tool usage:**Create,select,and apply appropriate techniques,resources,and modern Engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations. |
| **PO6** | **The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal,health,safety,legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice. |
| **PO7** | **Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need For sustainable development. |
| **PO8** | **Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice. |
| **PO9** | **Individual and team work:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings. |
| **PO10** | **Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and Receive clear instructions. |
| **PO11** | **Project management and finance:** Demonstrate knowledge and understanding of the Engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments. |
| **PO12** | **Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change. |
| **PROGRAM SPECIFIC OUTCOMES(PSOs)** | |
| **PSO1** | To develop software projects using standard practices and suitable programming environment. |
| **PSO2** | To identify, formulate and solve the real life problems faced in the society, industry and other areas by applying the skills of the programming languages, networks and databases learned. |
| **PSO3** | To applycomputerscienceknowledgeinexploringandadoptinglatesttechnologiesin various inter-disciplinary research activities. |

Cos MAPPING WITH POs& PSOs((R22CSM3112) MACHINE LEARNING))

At the end of the course student will be able to:

| | |
|---|---|
| **C325.1** | Understand The machine learning(Understanding) |
| **C325.2** | Understand The ANN(Understanding) |
| **C325.3** | Understand the bayes theorem &knn(Understanding) |
| **C325.4** | Know about the Genetis Algo's & Fuzzy Logic(Analyze) |
| **C325.5** | Applying inductive and analytical learning(Applying) |

**Course Articulation Matrix**

| Course Outcome | PO1 | PO2 | PO3 | PO4 | PO5 | PO6 | PO7 | PO8 | PO9 | PO10 | PO11 | PO12 | PSO1 | PSO2 | PSO3 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C325.1** | 3 | - | - | 3 | - | - | - | - | - | - | - | 2 | 3 | 3 | - |
| **C325.2** | 3 | - | - | 3 | - | - | - | - | - | - | - | - | 3 | 2 | - |
| **C325.3** | 3 | 2 | 3 | 2 | 3 | - | - | - | - | - | - | 2 | 3 | 3 | - |
| **C325.4** | 3 | - | 3 | 3 | - | - | - | - | - | - | - | 2 | 3 | 3 | - |
| **C325.5** | 3 | - | - | - | - | - | - | - | - | - | - | 2 | 3 | 2 | - |
| **C325** | **3** | **2** | **3** | **2.7** | **3** | **-** | **-** | **-** | **-** | **-** | **-** | **2** | **3** | **2.6** | **3** |

SRI INDU COLLEGE OF ENGINEERING & TECHNOLOGY
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Sheriguda (V), Ibrahimpatnam, R.R.Dist, Hyderabad - 501 510

D4

**BR-22**

**Lr.No.SICET/AUTO/DAE/III B.Tech Academic Calendar/85/2024**

# B.TECH III-YEAR I-SEM & II-SEM ACADEMIC CALENDAR
## (FOR ACADEMIC YEAR : 2024-25)

## Academic Calendar for B.Tech – III[rd] Year Students (2022 - 23 Batch), BR-22 Regulation.

## I – Semester

| S.No. | EVENT | PERIOD | DURATION |
|---|---|---|---|
| 1. | **Commencement of class work.** | **22.07.2024 (Monday)** | |
| 2. | 1st Spell of Instructions for covering First Two and a half Units.(Including CRT training Classes) | 22.07.2024 – 28.09.2024 | 10 Weeks |
| 3. | I Mid Term Examinations. | 30.09.2024 – 05.10.2024 | 5 Days |
| 4. | Submission of I Mid Term Examination Marks. | 09.10.2024 | |
| 5. | 2nd Spell of Instructions for Remaining Two and a half Units. | 14.10.2024 – 14.12.2024 | 9 Weeks |
| 6. | II Mid Term Examinations. | 16.12.2024 – 18.12.2024 | 3 Days |
| 7. | Preparation Holidays and Practical Examinations | 19.12.2024 – 28.12.2024 | 1 Week 3 Days |
| 8. | Submission of II Mid Term Examination Marks. | 27.12.2024 | |
| 9. | I Semester End Examinations. | 30.12.2024 – 18.01.2025 | 3 Weeks |
| **Commencement of Class-Work for III B.Tech - II Semester 20.01.2025 (Monday)** | | | |

**Note: No of Working/instructional days : 99**

## II – Semester

| S.No. | EVENT | PERIOD | DURATION |
|---|---|---|---|
| 1. | **Commencement of class work.** | **20.01.2025 (Monday)** | |
| 2. | 1st Spell of Instructions for covering First Two and a half Units. | 20.01.2025 – 22.03.2025 | 9 Weeks |
| 3. | I Mid Term Examinations. | 24.03.2025 – 26.03.2025 | 3 Days |
| 4. | Submission of I Mid Term Examination Marks. | 02.04.2025 | |
| 5. | 2nd Spell of Instructions for Remaining Two and a half Units. | 27.03.2025 – 10.05.2025 | 6 Weeks 3 Days |
| 6. | Summer Vacation | 12.05.2025 – 24.05.2025 | 2 Weeks |
| 7. | Continuation of 2nd Spell of Instructions for Remaining Two and a half Units. | 26.05.2025 – 11.06.2025 | 2 Weeks 3 Days |
| 8. | II Mid Term Examinations. | 12.06.2025 – 14.06.2025 | 3 Days |
| 9. | Preparation Holidays and Practical Examinations | 16.06.2025 – 21.06.2025 | 1 Week |
| 10. | Submission of II Mid Term Examination Marks. | 19.06.2025 | |
| 11. | II Semester End Examinations | 23.06.2025 – 05.07.2025 | 2 Weeks |
| 12. | Commencement of Class-Work for IV B.Tech - I Semester | 07.07.2025(Monday) | |

**Note: No of Working/instructional days : 98**

**ACE** **CE** **DIRECTOR** **PRINCIPAL**

Controller of Examination
Sri Indu College of Engineering & Technology
(An Autonomous Institution Under UGC)
Sheriguda (V), Ibrahimpatnam, R.R. Dist-501510.

DIRECTOR
Sri Indu College of Engineering & Technology
(An Autonomous Institution Under UGC)
Sheriguda (V), Ibrahimpatnam, R.R. Dist-501510.

PRINCIPAL
Sri Indu College of Engineering & Technology
(An Autonomous Institution Under UGC)
Sheriguda (V), Ibrahimpatnam, R.R. Dist-501510.

Sign:
**Dr. M.V.S.S. Giridhar**
Prof. of CEA; JNTUH Nominee

Sign:
**Dr. T. Venu Gopal**
Prof. of CSE; JNTUH Nominee

Sign:
**Dr. D. Ramesh**
Prof. of CSE; JNTUH Nominee

**(Copy to DAP&E and Copy to all the Dept. Heads)**

# Sri Indu College of Engineering&Technology

(An Autonomous Institution under UGC)

Sheriguda (V), Ibrahimpatnam(M),Ranga Reddy(Dist)–501 510

## Department of AIDS

ROOMNO:402 & 403

Class: III AIDS-A & B (II-SEM)

## Time-Table

**w.e.f:20-01-2025**

# Sri Indu College of Engineering and Technology

(An Autonomous Institution under UGC)
Sheriguda (V), Ibrahimpatnam (M), Ranga Reddy (Dist) – 501 510

## Department of Artificial Intelligence & Data Science

ROOM NO: Main 403
Class: III AI&DS (II SEM) Section – A **Time - Table**

w.e.f:20-01-2025

| Days /Time | 9:40 – 10:40 | 10:40 – 11:40 | 11:40 – 12:40 | 12:40 To 1:20 | 1:20 – 2:15 | 2:15 – 3:10 | 3:10 – 4:00 |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | | 4 | 5 | 6 |
| Monday | ML | ATCD | BDA | LUNCH | ITE | STM | ES |
| Tuesday | ATCD | BDA | STM | | ML LAB | | |
| Wednesday | ES | ATCD | STM | | ML | BDA | ITE |
| Thursday | BDA LAB | | | | STM | ATCD | ITE |
| Friday | BDA | ITE | ML | | SDC LAB | | |
| Saturday | ITE | ML | STM | | ATCD | ML | BDA |

| SUBJECT CODE | SUBJECT NAME | NAME OF THE FACULTY |
|---|---|---|
| R22CSM2212 | Automata Theory and Compiler Design(ATCD) | A.Venu Madhavi |
| R22CSM3112 | Machine Learning(ML) | K.Madhav Reddy |
| R22CSD3213 | Big Data Analytics(BDA) | M.Jyothi Redddy |
| R22CSE3244 | Software Testing Methodologies(STM) | T.Tejaswi |
| R22INF3235 | Information Technology Essentials(ITE) | B.Gouthami |
| R22CSM3126 | Machine Learning Lab(ML LAB) | K.Madhav Reddy & K. Vijay Kumar |
| R22CSD3227 | Big Data Analytics Lab()BD LAB | M.Jyothi Reddy & K.Nagarjuna |
| R22AID3268 | Industrial Oriented Mini Project/Internship/Skill Development Course(UI design-Flutter)(SDC) | B.Gouthami & Anil Kumar |
| R22MAC1110 | Environmental Science(ES) | Dr.Ajazdar |

CO-ORDINATOR HOD PRINCIPAL

# Sri Indu College of Engineering and Technology

(An Autonomous Institution under UGC)
Sheriguda (V), Ibrahimpatnam (M), Ranga Reddy (Dist) – 501 510

## Department of Artificial Intelligence & Data Science

ROOM NO: Main 403
Class: III AI&DS (II SEM) Section - B

## Time - Table

w.e.f:20-01-2025

| Days /Time | 9:40 – 10:40 | 10:40 – 11:40 | 11:40 – 12:40 | 12:40 To 1:20 | 1:20 – 2:15 | 2:15 – 3:10 | 3:10 – 4:00 |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | | 4 | 5 | 6 |
| Monday | ITE | ES | ATCD | | STM | ML | BDA |
| Tuesday | SDC LAB | | | | ATCD | BDA | STM |
| Wednesday | BDA LAB | | | | BDA | ITE | ML |
| Thursday | STM | ML | ITE | | ML LAB | | |
| Friday | ITE | ATCD | ES | | STM | ATCD | ML |
| Saturday | BDA | ITE | ML | | BDA | ATCD | STM |

LUNCH

| SUBJECT CODE | SUBJECT NAME | NAME OF THE FACULTY |
|---|---|---|
| R22CSM2212 | Automata Theory and Compiler Design(ATCD) | A.Venu Madhavi |
| R22CSM3112 | Machine Learning(ML) | R.Madhava Reddy |
| R22CSD3213 | Big Data Analytics(BDA) | M.Jyothi Redddy |
| R22CSE3244 | Software Testing Methodologies(STM) | T.Tejaswi |
| R22INF3235 | Information Technology Essentials(ITE) | B.Gouthami |
| R22CSM3126 | Machine Learning Lab(ML LAB) | K.Madhav Reddy & K. Vijay Kumar |
| R22CSD3227 | Big Data Analytics Lab(BD LAB) | M.Jyothi Reddy & K.Nagarjuna |
| R22AID3268 | Industrial Oriented Mini Project/Internship/Skill Development Course(UI design-Flutter)(SDC) | B.Gouthami & Anil Kumar |
| R22MAC1110 | Environmental Science(ES) | Dr.Ajazdar |

CO-ORDINATOR HOD PRINCIPAL

# *MACHINE LEARNING*

BR22 – B.TECH. –ARTIFICIAL INTELLIGENCE & DATA SCIENCE
SRI INDU COLLEGE OF ENGINEERING & TECHNOLOGY (AUTONOMOUS)
B.Tech. - III Year –II Semester

**L T P C**
**3 0 0 3**

## (R22CSM3112) MACHINE LEARNING

Course Objectives

- This course explains machine learning techniques such as decision tree learning, Bayesian learning etc.
- To understand computational learning theory.
- To study the pattern comparison techniques.

Course Outcomes

1. Ability to formulate machine learning problems corresponding to different applications.
2. Appreciate the underlying mathematical relationships within and across Machine Learning algorithms and the paradigms of supervised and un-supervised learning.
3. To understand the basic theory underlying machine learning.
4. Learn the concept of Hypothesis.
5. Understand the learning rules.
6. Ability to understand the Analytical Learning.

UNIT - I

Introduction - Well-posed learning problems, designing a learning system, Perspectives and issues in machine learning.

Concept learning and the general to specific ordering – introduction, a concept learning task, concept learning as search, find-S: finding a maximally specific hypothesis, version spaces and the candidate elimination algorithm, remarks on version spaces and candidate elimination, inductive bias.

Decision Tree Learning–Introduction, decision tree representation, appropriate problems for decision tree learning, the basic decision tree learning algorithm, hypothesis space search in decision tree learning, inductive bias in decision tree learning, issues in decision tree learning.

UNIT - II

Artificial Neural Networks-1– Introduction, neural network representation, appropriate problems for neural network learning, perceptions, multilayer networks and the back-propagation algorithm.

Artificial Neural Networks-2- Remarks on the Back-Propagation algorithm, An illustrative example: face recognition, advanced topics in artificial neural networks.

Evaluation Hypotheses – Motivation, estimation hypothesis accuracy, basics of sampling theory, a general approach for deriving confidence intervals, difference in error of two hypotheses, comparing learning algorithms.

UNIT - III

Bayesian learning – Introduction, Bayes theorem, Bayes theorem and concept learning, Maximum Likelihood and least squared error hypotheses, maximum likelihood hypotheses for predicting probabilities, minimum description length principle, Bayes optimal classifier, Gibs algorithm, Naïve Bayes classifier, an example: learning to classify text, Bayesian belief networks, the EM algorithm.

Computational learning Theory–Introduction, probably learning an approximately correct hypothesis, sample complexity for finite hypothesis space, sample complexity for infinite hypothesis spaces, the mistake bound model of learning.

Instance-Based Learning- Introduction, k-nearest neighbour algorithm, locally weighted regression, radial basis functions, case-based reasoning, remarks on lazy and eager learning.

UNIT- IV Genetic Algorithms – Motivation, Genetic algorithms, an illustrative example, hypothesis space search, genetic programming, models of evolution and learning, parallelizing genetic algorithms.
Learning Sets of Rules – Introduction, sequential covering algorithms, learning rule sets: summary, learning First-Order rules, learning sets of First-Order rules: FOIL, Induction as inverted deduction, inverting resolution.
Reinforcement Learning–Introduction, the learning ask, Q–learning ,non-deterministic , rewards and actions, temporal difference learning, generalizing from examples, relationship to dynamic programming.

UNIT - V Analytical Learning-1- Introduction, learning with perfect domain theories: PROLOG-EBG, remarks on explanation-based learning, explanation-based learning of search control knowledge.
Analytical Learning-2-Using prior knowledge to alter the search objective, using prior knowledge to augment search operators.
Combining Inductive and Analytical Learning – Motivation, inductive-analytical approaches to learning, using prior knowledge to initialize the hypothesis.

TEXT BOOK: 1. Machine Learning – Tom M. Mitchell, - MGH.

REFERENCE BOOK: 1. Machine Learning: An Algorithmic Perspective, Stephen Marshland, Taylor & Francis.

| | | |
|---|---|---|
| | **SRI INDU COLLEGE OF ENGG&TECH**<br>**LESSON PLAN**<br>**(Regulation:R22)**<br>**Department of AIDS** | **PreparedonRev 1:**<br>**Page:1of 2** |

| | | |
|---|---|---|
| **Sub.Code&Title** | **(R22CSM3112) MACHINE LEARNING** | (R22CSM3112) MACHINE LEARNING |

| | | |
|---|---|---|
| **Academic Year:2024-25** | **Year/Sem./Section** | **III-II/A & B** |
| **Faculty Name & Designation** | **R. MADHAVA REDDY& Assistant Professor** | |

| Unit/ Item No. | Topic(s) | Book Reference | Page(s) From | Page(s) To | Teaching Methodology | Proposed No. of Periods | Proposed Date of Handled | CO/RBT |
|---|---|---|---|---|---|---|---|---|
| | **UNIT-I** | | | | | | | |
| 1.1 | Introduction - Well-posed learning problems | T1,R1 | 1 | 4 | PPT | 1 | | CO1 |
| 1.2 | Designing a learning system, Perspectives and issues in machine learning. | T1,R1 | 4 | 6 | BlackBoard | 1 | | CO1 |
| 1.3 | Concept learning and the general to specific ordering – introduction | R1 | 6 | 10 | BlackBoard | 1 | | CO1 |
| 1.4 | A concept learning task, concept learning as search, | T1,R1 | W1 | W1 | BlackBoard | 1 | | CO1 |
| 1.5 | find-S: finding a maximally specific hypothesis | T1 | 15 | 17 | PPT | 1 | | CO1 |
| 1.6 | Version spaces and the candidate elimination algorithm | T1 | 18 | 19 | BlackBoard | 1 | | CO1 |
| 1.7 | Remarks on version spaces and candidate elimination, inductive bias. | R1 | 20 | 21 | BlackBoard | 1 | | CO1 |
| 1.8 | Decision Tree Learning–Introduction | R1 | 22 | 24 | BlackBoard | 1 | | CO1 |
| 1.9 | Decision tree representation | R1 | 25 | 27 | PPT | 1 | | CO1 |
| 1.10 | Appropriate problems for decision tree learning | R1 | 28 | 30 | BlackBoard | 1 | | CO1 |
| 1.11 | The basic decision tree learning algorithm | T1 | 31 | 34 | BlackBoard | 1 | | CO1 |
| 1.12 | Hypothesis space search in decision tree learning | T1 | 31 | 34 | BlackBoard | 1 | | CO1 |
| 1.13 | Inductive bias in decision tree learning | T1 | 31 | 34 | BlackBoard | 2 | | CO1 |
| 1.14 | Issues in decision tree learning. | T1 | 31 | 34 | BlackBoard | 1 | | CO1 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **UNIT-II** | | | | | | | | |
| 2.1 | Artificial Neural Networks-1– Introduction | T1 | 43 | 48 | BlackBoard | 1 | | CO2 |
| 2.2 | Neural network representation, appropriate problems for neural network learning | T1 | 49 | 54 | PPT | 2 | | CO2 |
| 2.3 | Perceptions, multilayer networks | T1 | 55 | 57 | BlackBoard | 1 | | CO2 |
| 2.4 | The back-propagation algorithm | T1 | 58 | 62 | BlackBoard | 2 | | CO2 |
| 2.5 | Artificial Neural Networks-2- Remarks on the Back-Propagation algorithm | T1 | 62 | 65 | BlackBoard | 1 | | CO2 |
| 2.6 | An illustrative example: face recognition | T1 | 66 | 68 | BlackBoard | 2 | | CO2 |
| 2.7 | Advanced topics in artificial neural networks | T1 | 69 | 72 | BlackBoard | 1 | | CO2 |
| 2.8 | Evaluation Hypotheses – Motivation, estimation hypothesis accuracy | T1 | 73 | 76 | BlackBoard | 1 | | CO2 |
| 2.9 | Basics of sampling theory, a general approach for deriving confidence intervals | T1 | 76 | 79 | PPT | 2 | | CO2 |
| 2.10 | Difference in error of two hypotheses, comparing learning algorithms. | T1 | 80 | 83 | BlackBoard | 1 | | CO2 |
| **UNIT-III** | | | | | | | | |
| 3.1 | Bayesian learning – Introduction, Bayes theorem | T1 | 101 | 106 | BlackBoard | 1 | | CO3 |
| 3.2 | Bayes theorem and concept learning, Maximum Likelihood and least squared error hypotheses | T1 | 106 | 109 | PPT | 2 | | CO3 |
| 3.3 | Maximum likelihood hypotheses for predicting probabilities, minimum description length principle | T1 | 109 | 112 | PPT | 2 | | CO3 |
| 3.4 | Bayes optimal classifier, Gibs algorithm | T1 | 113 | 114 | BlackBoard | 1 | | CO3 |
| 3.5 | Naïve Bayes classifier, an example: learning to classify text | T1 | 118 | 120 | BlackBoard | 2 | | CO3 |
| 3.6 | Bayesian belief networks, the EM algorithm | T1 | 121 | 125 | BlackBoard | 1 | | CO3 |
| 3.7 | Computational learning Theory–Introduction | T1 | 126 | 127 | BlackBoard | 1 | | CO3 |
| 3.8 | Probably learning an approximately correct hypothesis, sample complexity for finite hypothesis space | T1 | 129 | 128 | PPT | 1 | | CO3 |
| 3.9 | Sample complexity for infinite hypothesis spaces, the mistake bound model of learning | T1 | 126 | 127 | BlackBoard | 1 | | CO3 |
| 3.10 | Instance-Based Learning- Introduction, k-nearest neighbour algorithm | T1 | 129 | 128 | PPT | 1 | | CO3 |
| 3.11 | Locally weighted regression, radial basis functions, case-based reasoning, remarks on lazy and eager learning | T1 | 126 | 127 | BlackBoard | 1 | | CO3 |
| **UNIT-IV** | | | | | | | | |
| 4.1 | Genetic Algorithms – Motivation, Genetic algorithms | T1 | 150 | 153 | PPT | 2 | | CO4 |
| 4.2 | An illustrative example, hypothesis space search | T1 | W4 | W4 | PPT | 1 | | CO4 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 4.3 | Genetic programming, models of evolution and learning, parallelizing genetic algorithms | T1 | 157 | 160 | BlackBoard | 2 | | CO4 |
| 4.4 | Learning Sets of Rules – Introduction, sequential covering algorithms | T1 | W2 | W2 | BlackBoard | 1 | | CO4 |
| 4.5 | Learning rule sets: summary, learning First-Order rules | T1 | W2 | W2 | BlackBoard | 1 | | CO4 |
| 4.6 | Learning sets of First-Order rules: FOIL, Induction as inverted deduction, inverting resolution | T1 | W2 | W2 | BlackBoard | 3 | | CO4 |
| 4.7 | Reinforcement Learning–Introduction, the learning ask, Q–learning ,non-deterministic | T1 | W2 | W2 | PPT | 2 | | CO4 |
| 4.8 | Rewards and actions, temporal difference learning, generalizing from examples, relationship to dynamic programming. | T1 | W2 | W2 | BlackBoard | 2 | | CO4 |
| | **UNIT-V** | | | | | | | |
| 5.1 | Analytical Learning-1- Introduction, learning with perfect domain theories: PROLOG-EBG | **T1** | 166 | 170 | PPT | 3 | | CO5 |
| 5.2 | Remarks on explanation-based learning, explanation-based learning of search control knowledge | T1 | 172 | 175 | BlackBoard | 3 | | CO5 |
| 5.3 | Analytical Learning-2-Using prior knowledge to alter the search objective | T1 | 177 | 180 | BlackBoard | 2 | | CO5 |
| 5.4 | Using prior knowledge to augment search operators. | T1 | W5 | W5 | BlackBoard | 2 | | CO5 |
| 5.5 | Combining Inductive and Analytical Learning – Motivation, inductive-analytical approaches to learning | T1 | W5 | W5 | BlackBoard | 3 | | CO5 |
| 5.6 | Using prior knowledge to initialize the hypothesis. | T1,W1 | 19 | 185 | BlackBoard | 1 | | CO5 |
| | **Review** | **Signature of the HOD/Coordinator** | | | | | | |

**Expected Total No. of classes= =70/71**

## LIST OF TEXT BOOKS AND REFERENCES

TEXT BOOK:

1. Machine Learning – Tom M. Mitchell, - MGH.

REFERENCE BOOK:

1. Machine Learning: An Algorithmic Perspective, Stephen Marshland, Taylor & Francis

**Weblinks:**

**W1:** https://www.geeksforgeeks.org/machine-learning/well-posed-learning-problems/
W2: chatgpt

# ASSIGNMENT

| | | |
|---|---|---|
| | **SRI INDU COLLEGE OF ENGG& TECH**<br>**LESSON PLAN**<br>**(Regulation:R22)**<br>**Department of AIDS** | **(Regulation:R22)**<br>**Prepared on Rev1:**<br>**Page:5of6** |

| | | | |
|---|---|---|---|
| **Sub.Code&Title** | **(R22CSM3112)MACHINE LEARNING** | | |
| **AcademicYear:2024-25** | | **Year/Sem./Section** | **III/II/A/B** |
| **FacultyName&Designation** | **R MADHAVA REDDY&Assistant Professor** | | |

| S.No. | Assignment Questions | Course Outcome | Books To be Referred | Date Of Announcement | Date Of Submission |
|---|---|---|---|---|---|
| 1 | What is a well-posed learning problem? Provide an example. | CO1 | T1 | | |
| 2 | What is an artificial neural network (ANN), and how does it function? | CO3 | T1 | | |
| 3 | Explain **Bayes' theorem** and its significance in machine learning. Provide an example to illustrate its use. | CO1 | T1 | | |
| 4 | Explain **Bayes' theorem** and its significance in machine learning. Provide an example to illustrate its use. | CO4 | T1 | | |
| 5 | Compare and contrast Inductive Learning and Analytical Learning in Machine Learning. Illustrate with one real-world application example for each. Which type of learning is more suitable for situations with limited data? Justify your answer. | CO2 | T1 | | |

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| | **SRIINDUCOLLEGEOFENGG&TECHQ UESTIONBANK (Regulation :R22) Department Of CSE and AI&DS** | **(Regulation:R22)** |
| **Sub.Code&Title** | **(R22CSM3112)**MACHINE LEARNING | |
| **AcademicYear:2024-25** | **Year/Sem.** | III-II/AI&DS(A/B) |
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QUESTION BANK WITH BLOOMS TAXONOMY LEVEL (BTL)

(1. Remembering 2. Understanding 3. Applying 4. Analyzing 5. Evaluating 6. Creating)

| **UNIT-1 : INTRODUCTION** | | | |
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| | **Multiple choice Questions** | **BT Level** | **Course Outcome** |
| 1C-1 | What is Machine learning?<br>a) The selective acquisition of knowledge through the use of computer programs<br>b) The selective acquisition of knowledge through the use of manual programs<br>c) The autonomous acquisition of knowledge through the use of computer programs<br>d) The autonomous acquisition of knowledge through the use of manual programs | I | CO1 |
| 1C-2 | _____is the approach of basic algorithm for decision tree induction.<br>A) Greedy<br>b)Top Down<br>c)Procedural<br>d)Step by Step | I | CO1 |
| 1C-3 | Which of the following is not a supervised machine learning algorithm?<br>a) K-means<br>b) Naïve Bayes<br>c) SVM for classification problems<br>d)Decision tree | I | CO1 |
| 1C 4 | Well posed learning problems are<br>A) Chekers game<br>B) Handwriting recognition learning problem<br>C) Robo driving learning problem<br>D) All the above | I | CO1 |
| 1C-5 | Which algorithm is best suited for a binary classification problem?<br>a) K-nearest Neighbors<br>b) Decision Trees<br>c) Random Forest<br>d) Linear Regression | II | CO1 |
| 1C -6 | What is one of the drawbacks of the Find-S algorithm?<br>a) Computation cost is high<br>b) Time-ineffective<br>c) All correct hypotheses are not output.<br>d) Most specific accurate hypothesis is not output | I | CO1 |

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| 1C-6 | Decision tree uses the inductive learning machine learning approach.<br>A) False<br>B) True | I | CO1 |
| 1C-7 | What elements describe the Candidate-Elimination algorithm?<br>a) depends on the dataset<br>b) just a set of candidate hypotheses<br>c) just a set of instances<br>d) set of instances, set of candidate hypotheses | I | CO1 |
| 1C-8 | What is the goal of concept learning?<br>a) To minimize cross-validation set error<br>b) To maximize test set accuracy<br>c) To find a hypothesis that is most suitable for training instances<br>To identify all possible predictors | I | CO1 |
| 1C-9 | For a dataset with 4 attributes, which is the most general hypothesis?<br>a) (Sunny, Warm, Strong, Humid)<br>b) (Sunny, ?, ?, ?)<br>c) (?, ?, ?, ?)<br>d) (∅, ∅,∅,∅) | I | CO1 |
| 1C-10 | What is present in the version space of the Find-S algorithm in the beginning?<br>a) Set of all hypotheses H<br>b) Both maximally general and maximally specific hypotheses<br>c) Maximally general hypothesis<br>d) Maximally specific hypothesis | I | CO1 |
| 1C-11 | What is one of the assumption of the Find-S algorithm?<br>a) No assumptions are made<br>b) The most specific hypothesis is also the most general hypothesis<br>c) All training data are correct (there is no noise)<br>d)Overfitting does not occur | I | CO1 |
| 1C-12 | How does the hypothesis change gradually?<br>a) Specific to Specific<br>b) Specific to General<br>c) General to Specific<br>d)General to General | I | CO1 |
| 1C-14 | Which of the following statements is not true about the ID3 algorithm?<br>a) It is used to generate a decision tree from a dataset<br>b) It begins with the original set S as the root node<br>c) On each iteration of the algorithm, it iterates through every unused attribute of the set S and calculates the entropy or the information gain of that attribute<br>d) Finally it selects the attribute which has the largest entropy value | I | CO1 |
| 1C-15 | Which of the following statements is not true about Information Gain?<br>a) It is a gain measure that is used in the ID3 algorithms<br>b) It is the difference between the entropy of the label before and after the split<br>c) It is based on the decrease in entropy after a data-set is split on an attribute<br>d) Constructing a decision tree is all about finding attribute that returns the lowest information gain | I | CO1 |
| | **FILL IN TH E BLANKS** | **BT Level** | **Course** |

| | | | Outcome |
|---|---|---|---|
| IF- 1 | _____algorithm is best suited for a binary classification problem | I | CO1 |
| 1F-2 | _____ is a generative model used in machine learning | II | CO1 |
| 1F-3 | Candidate-Elimination algorithm can be described by _____ | I | CO1 |
| 1F-4 | version space represented by ____ | I | CO1 |
| 1F-5 | S = <sunny, warm, high, same>. Training data = <sunny, warm, normal, same> => Yes (positive example). How will S be represented after encountering this training data ---------- | I | CO1 |
| 1F-6 | version space of the Find-S algorithm in the beginning by_____ | II | CO1 |
| 1F-7 | What is one of the advantages of the Find-S algorithm__ | I | CO1 |
| 1F-8 | one of the drawbacks of the Find-S algorithm____ | II | CO1 |
| 1F-9 | Which algorithm accommodates all the maximally specific hypotheses_____ | I | CO1 |
| 1F-10 | Decision trees are a type of_ _____learning | I | CO1 |
| 1F-11 | Well posed learning problem if it has three traits_____. | I | CO1 |
| 1F-12 | Algorithm for version space_____. | I | CO1 |
| 1F-13 | Each leaf node represents the_____ | I | CO1 |
| 1F-14 | _____ is Consistent hypothesis . | I | CO1 |
| 1F-15 | | | |
| 1M-1 | Match the following<br>1. Machine learning<br>2. Supervised learning<br>3. Unsupervised learning<br>4. Backup and Recovery<br>A. Minimize errors in predictions<br>B. The predicted category of an input<br>C. Technique for teaching computers to learn from data<br>D. K-Means Clustering | I | CO1 |
| 1M -2 | 1) Cross Validation<br>2) Regularization<br>3) Precision<br>4) Recall<br>A. Precision focuses on false positives<br>B. recall focuses on false negatives<br>C. Testing a model's generalization ability<br>D. To decrease model complexity | II | CO1 |
| 1M -3 | 1) Find-S algorithm<br>2) Hypothesis<br>3) Find-S algorithm drawbacks<br>4) Hypothesis in FIND S<br>A. Positive Example inconsistent with the hypothesis is encountered<br>B. Computation cost is high<br>C.Maximally specific hypothesis<br>D. Specific to General | II | CO1 |
| 1M -4 | 1) Well posed learning<br>2) Decision Tree<br>3) Training Example<br>4) Version Space<br>A. Candidate elimination algorithm<br>B. Checker's game<br>C. Information Gain<br>D. Target attribute | I | CO1 |

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| 1M -5 | 1) ID3<br>2) P+<br>3) Entrophy<br>4) Occam's Razor<br>A. Prefer the simplest hypothesis that fits the data<br>B. Searches a complete hypothesis space<br>C. Proportion of positive examples<br>D. Information gain | II | CO1 |
| | **5-MARKSQUESTIONS** | **BT Level** | **Course Outcome** |
| 1D-1. | Define Machine Learning. Explain with examples why machine learning is important. | II | CO1 |
| 1D-2. | Describe the following problems with respect to Tasks,Performance and Experience:<br>A. A Checkers learning problem<br>B. Handwritten recognition learning problem<br>C.A Robot driving learning problem | I | CO1 |
| 1D-3. | Apply FIND-S algorithm and explain with example given below | III | CO1 |
| 1D-4. | Determine the version space for the above mentioned training examples using candidate elimination algorithm. | V | CO1 |
| 1D-5. | Explain in detail the Inductive Bias of Candidate Elimination algorithm | II | CO1 |
| 1D-6. | Construct the Decision tree for the following set of training examples | III | CO1 |
| 1D-7. | Define Consistent Hypothesis and Version Space. | I | CO1 |
| 1D-8 | Discuss Inductive Bias in DecisionTree Learning and explain the Restriction Biases, Preference Biases. | VI | CO1 |
| 1D-9 | Consider the following set of training examples.<br>a) What is the entropy of this collection of training example with respect to the Target function classification?<br>b) What is the information gain of training examples? | I | CO1 |

| Example | Sky | AirTemp | Humidity | Wind | Water | Forecast | Enjoy Sport |
|---|---|---|---|---|---|---|---|
| 1 | Sunny | Warm | Normal | Strong | Warm | Same | Yes |
| 2 | Sunny | Warm | High | Strong | Warm | Same | Yes |
| 3 | Rainy | Cold | High | Strong | Warm | Change | No |
| 4 | Sunny | Warm | High | Strong | Cool | Change | Yes |

| Day | Outlook | Temperature | Humidity | Wind | Play Tennis |
|---|---|---|---|---|---|
| D1 | Sunny | Hot | High | Weak | No |
| D2 | Sunny | Hot | High | Strong | No |
| D3 | Overcast | Hot | High | Weak | Yes |
| D4 | Rain | Mild | High | Weak | Yes |
| D5 | Rain | Cool | Normal | Weak | Yes |
| D6 | Rain | Cool | Normal | Strong | No |
| D7 | Overcast | Cool | Normal | Strong | Yes |
| D8 | Sunny | Mild | High | Weak | No |
| D9 | Sunny | Cool | Normal | Weak | Yes |
| D10 | Rain | Mild | Normal | Weak | Yes |
| D11 | Sunny | Mild | Normal | Strong | Yes |
| D12 | Overcast | Mild | High | Strong | Yes |
| D13 | Overcast | Hot | Normal | Weak | Yes |
| D14 | Rain | Mild | High | Strong | No |

| Instance | Classification | $a_1$ | $a_2$ |
|---|---|---|---|

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| | | | | | | |
| | 1 | + | T | T | | |
| | 2 | + | T | T | | |
| | 3 | - | T | F | | |
| | 4 | + | F | F | | |
| | 5 | - | F | T | | |
| | 6 | - | F | T | | |
| 1D-10 | Identify the entropy,information gain and draw the decision trees for the following set of training example. | | | | III | CO1 |
| | Gender | Car ownership | Travel cost | Income Level | Transpor tation (Class) | |
| | Male | 0 | Cheap | Low | Bus | |
| | Male | 1 | Cheap | Me dium | Bus | |
| | Female | 1 | Cheap | Me dium | Train | |
| | Female | 0 | Cheap | Low | Bus | |
| | Male | 1 | Cheap | Me dium | Bus | |
| | Male | 0 | Standard | Me dium | Train | |
| | Female | 1 | Standard | Me dium | Train | |
| | Female | 1 | Expensi ve | High | Car | |
| | Male | 2 | Expensi ve | Me dium | Car | |
| | Female | 2 | Expensi ve | High | Car | |
| 1D-11 | List and Interpret the issues in decision tree learning in detail. | | | | II | CO1 |
| 1D-12 | Explain basic decision tree algorithm with example? | | | | I | CO1 |
| | **UNIT-II** | | | | | |
| | **Multiple choice Questions** | | | | **BTLevel** | **Course Outcome** |
| 2C-1 | What is perceptron?<br>a) a single layer feed-forward neural network with pre-processing<br>b) an auto-associative neural network<br>c) a double layer auto-associative neural network<br>d) a neural network that contains feedback | | | | I | CO2 |
| 2C-2 | What is an Artificial Neural Network (ANN)?<br>a) A computational model inspired by the human brain<br>b) A machine learning algorithm used for image processing<br>c) A statistical analysis technique for data clustering<br>d) A programming language for neural network implementation | | | | I | CO2 |
| 2C-3 | What is the basic building block of an Artificial Neural Network?<br>a) Neuron<br>b) Activation function<br>c) Gradient descent<br>d) Loss function | | | | I | CO2 |

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| 2C-4 | Which of the following activation functions is commonly used in ANNs?<br>a) ReLU (Rectified Linear Unit)<br>b) Sigmoid<br>c) Tanh (Hyperbolic Tangent)<br>d) All of the above | I | CO2 |
| 2C-5 | What is the function of the input layer in an ANN?<br>a) It receives input data and passes it to the hidden layers<br>b) It performs mathematical computations on the input data<br>c) It stores the trained weights and biases of the network<br>d) None of the above | I | CO2 |
| 2C-6 | Which layer of an ANN is responsible for making predictions or producing the final output?<br>a) Input layer<br>b) Hidden layer<br>c) Output layer<br>d) All layers contribute equally | I | CO2 |
| 2C-7 | What is the purpose of the back propagation algorithm in ANN training?<br>a) To update the weights and biases based on the prediction error<br>b) To initialize the weights and biases of the network<br>c) To determine the number of hidden layers and neurons<br>d) None of the above | I | CO2 |
| 2C-8 | What is the purpose of the forward pass in ANN training?<br>a) To compute the predicted output based on the current weights and biases<br>b) To adjust the weights and biases using gradient descent<br>c) To identify misclassified samples and update the model<br>d) None of the above | I | CO2 |
| 2C-9 | What is the primary goal of training an ANN?<br>a) To minimize the prediction error on the training data<br>b) To maximize the number of neurons in the hidden layers<br>c) To achieve 100% accuracy on the test data<br>d) None of the above | I | CO2 |
| 2C-10 | Which of the following is a common optimization algorithm used in ANN training?<br>a) Gradient Descent<br>b) Stochastic Gradient Descent (SGD)<br>c) Adam<br>d) All of the above | I | CO2 |
| 2C-11 | Which type of ANN architecture is commonly used for image classification tasks?<br>a) Convolutional Neural Network (CNN)<br>b) Recurrent Neural Network (RNN)<br>c) Radial Basis Function Network (RBFN)<br>d) Multilayer Perceptron (MLP) | I | CO2 |
| 2C-12 | What is the purpose of weight initialization in ANN training?<br>a) To set the initial values of the weights and biases in the network<br>b) To adjust the learning rate during training<br>c) To compute the gradient of the loss function<br>d) None of the above | I | CO2 |

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| 2C-13 | Which activation function is commonly used in the output layer for binary classification in ANN's?<br>a) Sigmoid<br>b) ReLU (Rectified Linear Unit)<br>c) Tanh (Hyperbolic Tangent)<br>d) Softmax | I | CO2 |
| 2C-14 | What is the purpose of the bias term in an ANN?<br>a) To provide a threshold for neuron activation<br>b) To add an additional feature to the input data<br>c) To prevent over-fitting by adjusting the learning rate<br>d) None of the above | I | CO2 |
| 2C-15 | What is full form of ANN's?<br>a)Artificial Neural Node<br>b)AI Neural Networks<br>c)Artificial Neural Networks<br>d) Artificial Neural number | I | CO2 |
| | **Fill in the blanks** | | |
| 2F-1 | ANN is the collection of artificial _____ | II | CO2 |
| 2F-2 | In ANN, Neurons interconnected among multiple network layers are referred to as _____ | I | CO2 |
| 2F-3 | The complexity of ANN is dependent upon ---------- | | CO2 |
| 2F-4 | Weighted sums in ANNs are referred to as ---------- | I | CO2 |
| 2F-5 | Weighted sums are passed via activation functions and --------is produced | II | CO2 |
| 2F-6 | Ultimate results are produced in ANN at ---------- | I | CO2 |
| 2F-7 | Input applied in ANN passed on to layers hidden to produce outcome is referred to as ---------- | II | CO2 |
| 2F-8 | Computational power in ANNs is determined by ---------- | II | CO2 |
| 2F-9 | ANN involves large processors operating in ---------- | I | CO2 |
| 2F-10 | ANNs are ---------- | II | CO2 |
| 2F-11 | Facial recognitions & computer vision technologies use ---------- | II | CO2 |
| 2F-12 | Processing nodes outcome is saved in ----------variant of ANN | II | CO2 |
| 2F-13 | Text-to-speech conversion uses ---------- | I | CO2 |
| 2F-14 | Image recognition is possible by using ---------- | II | CO2 |
| 2F-15 | ANNs are utilized for Dynamic modelling and its identification ---------- | II | CO2 |
| | **Match the following** | | |
| 2M-1 | 1) Interconnected units<br>2) Input layer<br>3) Hidden layer<br>4) Output layer | A) Representing predictions or classifications<br>B) Nuerons<br>C) Recieves th einput data<br>D) Perform intermediate computations and transformations | II CO2 |

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| 2M-2 | 1) Artificial neural netwroks<br>2) ReLU activation function<br>3)Back propagation<br>4) Output layer | A) Collection of interconnected nodes or Nuerons<br>B)Recieves th einput data<br>C) An optimization algorithm for training neural networks<br>D) Perform intermediate computations and transformations | II | CO2 |
| 2M-3 | 1) Null hypothesis<br>2) Alternative hypothesis<br>3) Type I Error<br>4) Type II Error | A) A statement of an effect or a difference<br>B) A statement of no effect or no difference<br>C) Failing to reject the null hypothesis when it is false<br>D) Rejecting the null hypothesis when it is true. | II | CO2 |

**5-MARKSQUESTIONS**

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| 2D-1. | Elaborate multi layer networks and back propagation algorithm with an example. | VI | CO2 |
| 2D-2. | Consider two perceptron defined by the threshold expression w0 + wlxl+ w2x2 >0. PerceptronAhasweightvaluesw0=1, w1=2,w2=1 And perceptron B has the weigh tvalues w0=0, w1=2, w2=1True or false? PerceptronA is more-general than perceptronB. | II | CO2 |
| 2D-3. | Write a note on (i)Perceptron Training Rule (ii)Gradient Descent and Delta Rule. | I | CO2 |
| 2D-4. | How a single perceptron can be used to represent the Boolean functions such as AND& OR? Justify | | CO2 |
| 2D-5. | Design a two-input perceptron that implements the Boolean function A ∧¬B. Design a two-layer network of perceptron's that implements A XOR B | VI | CO2 |
| 2D-6. | Evaluate the practical design choices involved in applying backpropagation algorithm in learning task of face recognition system. | V | CO2 |
| 2D-7 | What are the remarks of Back Propagation Algorithm? Illustrate in detail. | I | CO2 |
| 2D-8 | Discuss in detail about representation of Neural Networks. | VI | CO2 |
| 2D-9 | Discuss how a multi-layer network learns using a gradient descent algorithm | VI | CO2 |
| 2D-10 | Distinguish between single layer and multilayer neural networks. | III | CO2 |
| 2D-11 | Present the Back propagation algorithm for feed forward networks and explain each step in it | II | CO2 |
| 2D-12 | Explain multilayer neural networks using back propagation with an example. | II | CO2 |
| 2D-13 | What is Artificial Neural Network? Explain appropriate problem for Neural Network Learning with its characteristics. | I | CO2 |

| | UNIT-III -MCQ'S | BT LEVEL | CO |
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| 3C-1 | What is the fundamental principle behind Bayesian algorithms?<br>a. Minimizing error<br>b. Maximizing accuracy<br>c. Incorporating prior knowledge<br>d. Optimizing computational complexity | I | CO3 |
| 3C-2 | Which Bayesian algorithm is commonly used for classification tasks?<br>a. Naive Bayes<br>b. Bayesian Networks<br>c. Bayesian Linear Regression<br>d. Bayesian Optimization | I | CO3 |
| 3C-3 | Which assumption does the Naive Bayes algorithm make regarding the features?<br>a. They are conditionally dependent<br>b. They are conditionally independent<br>c. They are normally distributed<br>d. They are uniformly distributed | I | CO3 |
| 3C-4 | Which Bayesian algorithm is commonly used for modelling dependencies among variables?<br>a. Naive Bayes<br>b. Bayesian Networks<br>c. Bayesian Linear Regression<br>d. Bayesian Optimization | I | CO3 |
| 3C-5 | K-Nearest Neighbours (KNN) is classified as what type of machine learning algorithm?<br>a) Instance-based learning<br>b) Parametric learning<br>c) Non-parametric learning<br>d) Model-based learning | I | CO3 |
| 3C-6 | k-nearest neighbour (k-NN) is a type of ____ method.<br>a) Reinforcement learning<br>b) Unsupervised learning<br>c) Instance-based learning<br>d) Lazy learning | I | CO3 |
| 3C-7 | Which of the following is a disadvantage of lazy learning?<br>a) Difficulty to maintain<br>b) Not fit for simultaneous application to multiple problems<br>c) Not suitable for complex and incomplete problem domains<br>d) Difficult to handle excessively noise data | I | CO4 |
| 3C-8 | Choose the instance-based learner.<br>A) Eager Learner<br>B) Lazy Learner<br>C) Both (A) and (B)<br>D) None of the Above | I | CO4 |

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| 3C-9 | How many terms are required for building a bayes model?<br>a) 1<br>b) 2<br>c) 3<br>d) 4 | I | CO4 |
| 3C-10 | Where does the bayes rule can be used?<br>A)Solving queries<br>B)Increasing complexity<br>C) Decreasing complexity<br>D) Answering probabilistic query | I | CO4 |
| 3C-11 | How the bayesian network can be used to answer any query?<br>A )Full distribution<br>B)Joint distribution<br>C)Partial distribution<br>D) All of the mentione | I | CO4 |
| 3C-12 | How the entries in the full joint probability distribution can be calculated?<br>A. Using variables<br>B. Using information<br>C. Both Using variables & information<br>D. None of the mentione | I | CO4 |
| 3C-13 | In the context of instance-based learning, what is an episodic memory?<br>A)A memory of specific instances in the training data<br>B)A memory of the general patterns in the training data<br>C)A memory of the similarity measures used during training<br>D) A memory of the classification rules learned during training | I | CO4 |
| 3C-14 | Which of the following is an example of Instance-Based Learning?<br>A) K-Nearest Neighbors<br>B) Naïve Bayes<br>C) Neural Networks<br>D) Decision Trees | I | CO4 |
| 3C-15 | What is the primary limitation of KNN?<br>A) High computational cost for large datasets<br>B) Cannot classify non-linear data<br>C) Requires labeled training data<br>D) Does not work with real-world problems | I | CO-4 |
| | **Fill in the Blanks** | **BT Level** | **Course Outcome** |
| 3F-1 | Bayes' theorem calculates the probability of a hypothesis given _____. | I | CO 3 |
| 3F-2 | The Gibbs Algorithm selects hypotheses based on their _____ probability. | I | CO 3 |
| 3F-3 | Naïve Bayes assumes that features are _____ of each other. | I | CO 3 |
| 3F-4 | The EM Algorithm is often used for training _____ models. | I | CO 3 |
| 3F-5 | Instance-based learning stores training examples and delays learning until a _____ is needed. | I | CO-4 |

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| 3F-6 | K-Nearest Neighbors finds the closest _____ to classify new data points. | I | CO-4 |
| 3F-7 | Case-Based Reasoning solves new problems by referring to _____ cases. | I | CO-4 |
| 3F-8 | Locally Weighted Regression assigns higher importance to _____ training points. | I | CO-4 |
| 3F-9 | The Minimum Description Length principle balances model complexity and _____. | I | CO-4 |
| 3F-10 | Naïve Bayes Algorithm is a _____learning algorithm. | I | CO-3 |
| 3F-11 | In the context of instance-based learning, what does the term `nan` refer to ---------- | I | CO-4 |
| 3F-12 | _____parameter of the K-Nearest Neighbors algorithm determines the number of neighbors to consider when classifying a new point | I | CO-4 |
| 3F-13 | Kind of data representation is commonly used in instance-based learning methods like K-Nearest Neighbors ---------- | I | CO-4 |

**5-MARKSQUESTIONS**

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| 3 D-1 | A)Explain the features of Bayesian learning methods.<br>B) Discuss the relationship between the maximum likelihood hypothesis and the least squared error hypothesis. | III | CO-3 |
| 3 D-2 | Illustrate Naïve Bayes Classifier of Bayesian learning. | II | CO-3 |
| 3 D-3 | Describe the Naive Bayesian method of classification. What assumptions does this method make about the ribues and the classification? Give an example where this assumption is to justify. | | CO-3 |
| 3 D-4 | Explain Gibs algorithm with an example. | II | CO-3 |
| 3 D-5 | State Bayes theorem. Illustrate Bayes theorem with an example. | II | CO-3 |
| 3 D-6 | a) Discuss about Bayesian belief networks.<br>b) Explain about Bayes theorem. | III | CO-3 |
| 3 D-7 | a) Explain Gibs algorithm with an example.<br>b) State and explain the Minimum Description Length Principle. | II | CO-3 |
| 3 D- 8 | Describe briefly about k-nearest neighbour algorithm | I | CO-4 |
| 3 D-9 | Compare and contrast Lazy and Eager Learning. | IV | CO-4 |
| 3 D-10 | Explain Weighted-Majority algorithm. | II | CO-4 |
| 3 D-11 | a) Write the differences between Eager Learning and Lazy Learning approaches.<br>b) State Bayes theorem. Illustrate Bayes theorem with an example. | I | CO-4 |
| 3 D-12 | Explain the Mistake Bound for the Halving Algorithm. | II | CO-4 |
| 3 D-13 | Elaborate the Locally Weighted Linear Regression. | VI | CO-4 |

UNIT-IV

| | Multiple choice Questions | BT Level | Course Outcome |
|---|---|---|---|

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| 4C-1 | What is the primary inspiration for Genetic Algorithms?<br>a) Neural networks<br>b) Evolution and natural selection<br>c) Decision trees<br>d) Bayesian networks | I | CO4 |
| 4C-2 | Which component of a genetic algorithm is responsible for maintaining diversity in the population?<br>a) Selection<br>b) Crossover<br>c) Mutation<br>d) Fitness function | I | CO4 |
| 4C-3 | How does a fitness function influence the genetic algorithm?<br>a) It assigns random values to solutions<br>b) It determines which individuals survive and reproduce<br>c) It removes weak solutions immediately<br>d) It generates new individuals through mutation | II | CO4 |
| 4C-4 | What is the main purpose of crossover in a genetic algorithm?<br>a) To increase population size<br>b) To create new offspring by combining genetic material from parents<br>c) To remove low-fitness individuals<br>d) To introduce random mutations | II | CO4 |
| 4C-5 | Which of the following approaches can parallelize genetic algorithms efficiently?<br>a) Using an island model<br>b) Reducing the population size<br>c) Removing the crossover operation<br>d) Avoiding mutation | III | CO4 |
| 4C-6 | You are given a hypothesis space in a genetic algorithm. How would you optimize the search?<br>a) Increase mutation probability to 100%<br>b) Use a fitness function that rewards diversity and performance<br>c) Always select the best individuals<br>d) Use only a single generation | III | CO4 |
| 4C-7 | How does genetic programming differ from standard genetic algorithms?<br>a) Genetic programming evolves programs as solutions<br>b) Genetic algorithms work only with binary chromosomes<br>c) Genetic programming requires labeled data<br>d) Genetic algorithms do not use mutation | IV | CO4 |
| 4C-8 | What is the main limitation of hypothesis space search in genetic algorithms?<br>a) It always converges to a global optimum<br>b) It can get stuck in local optima<br>c) It does not require a fitness function<br>d) It never explores new solutions | IV | CO4 |
| 4C-9 | Which of the following statements best describes the trade-off in genetic algorithms?<br>a) High mutation rates always lead to better results<br>b) Exploration and exploitation must be balanced<br>c) Crossover is always more important than mutation<br>d) Larger populations always result in faster convergence | V | CO4 |
| 4C-10 | When should genetic algorithms be preferred over traditional optimization methods?<br>a) When the problem has a smooth, differentiable function<br>b) When the search space is large and complex<br>c) When exact solutions are required<br>d) When deterministic results are needed | V | CO4 |
| 4C-11 | You are designing a reinforcement learning agent for a dynamic environment. How would you ensure it adapts to changes?<br>a) Keep the learning rate constant<br>b) Use a dynamic exploration-exploitation strategy<br>c) Remove rewards from the system<br>d) Reduce the number of possible actions | VI | CO4 |

| | | | |
|---|---|---|---|
| 4C-12 | What is the key idea behind Q-learning in reinforcement learning?<br>a) To compute the shortest path in a graph<br>b) To learn the optimal action-value function<br>c) To perform supervised learning<br>d) To minimize entropy | I | CO4 |
| 4C-13 | How does temporal difference learning differ from traditional reinforcement learning methods?<br>a) It updates values based on future rewards before the episode ends<br>b) It requires a complete model of the environment<br>c) It only works for deterministic environments<br>d) It cannot be applied to continuous state spaces | II | CO4 |
| 4C-14 | Which of the following techniques would best improve the efficiency of a sequential covering algorithm in rule learning?<br>a) Increasing the number of rules randomly<br>b) Using pruning strategies to remove redundant rules<br>c) Ignoring negative examples<br>d) Reducing the dataset size | III | CO4 |
| 4C-15 | How would you modify a standard reinforcement learning algorithm to handle multiple agents interacting in a competitive environment?<br>a) Use independent Q-learning for each agent<br>b) Eliminate exploration entirely<br>c) Reduce the state space<br>d) Use only positive rewards | VI | CO-4 |
| | **Fill in the Blanks** | BT Level | Course Outcome |
| 4F-1 | Genetic algorithms are inspired by the process of _____. | I | CO 4 |
| 4F-2 | The three main genetic operators in Genetic Algorithms are selection, _____, and mutation. | I | CO 4 |
| 4F-3 | In a genetic algorithm, the _____ function determines how well an individual solution performs in solving the problem. | II | CO 4 |
| 4F-4 | The purpose of mutation in Genetic Algorithms is to introduce _____ into the population to prevent premature convergence. | II | CO 4 |
| 4F-5 | The _____ model is a parallelization technique in genetic algorithms where multiple subpopulations evolve independently and occasionally exchange individuals. | III | CO-4 |
| 4F-6 | In reinforcement learning, the process of updating values based on estimated future rewards is called _____ learning. | III | CO-4 |
| 4F-7 | The primary challenge in hypothesis space search using Genetic Algorithms is avoiding _____, where the algorithm gets stuck in a suboptimal solution. | IV | CO-4 |
| 4F-8 | Genetic programming differs from genetic algorithms because it evolves _____ instead of fixed-length chromosomes. | IV | CO-4 |
| 4F-9 | The balance between exploration and exploitation in reinforcement learning is often managed using a parameter called _____. | V | CO-4 |
| 4F-10 | A major drawback of sequential covering algorithms is that they tend to generate overly _____ rule sets if not properly pruned. | V | CO-4 |
| 4F-11 | To improve Q-learning in environments with large state spaces, we can use function approximation techniques such as _____ networks. | VI | CO-4 |
| 4F-12 | The FOIL algorithm is used for learning _____ rules in machine learning. | I | CO-4 |

| | | | |
|---|---|---|---|
| 4F-13 | Inverting resolution is a technique used in learning sets of rules, where the goal is to derive a _____ representation of the knowledge. | II | CO-4 |
| 4F-14 | In reinforcement learning, the method that estimates the value of taking an action in a given state without requiring a model of the environment is called _____. | III | CO-4 |
| 4F-15 | A researcher wants to improve genetic algorithms by introducing a hybrid approach that combines evolution with gradient-based optimization. This technique is known as _____. | VI | CO-4 |

**5-MARKSQUESTIONS**

| | | | |
|---|---|---|---|
| 4 D-1 | Define a **Genetic Algorithm (GA)** and list its key components. | I | CO-4 |
| 4 D-2 | What is **hypothesis space search**, and how is it applied in Genetic Algorithms? | I | CO-4 |
| 4 D-3 | Explain how the fitness function influences the evolution process in Genetic Algorithms. | II | CO-4 |
| 4 D-4 | How does **genetic programming** differ from standard genetic algorithms? Provide an example of its application. | II | CO-4 |
| 4 D-5 | Describe the Island Model for parallelizing Genetic Algorithms and explain its advantages. | III | CO-4 |
| 4 D-6 | How can mutation and crossover rates be adjusted to improve the performance of a Genetic Algorithm? | III | CO-4 |
| 4 D-7 | Compare and contrast sequential covering algorithms and FOIL (First Order Inductive Learner) in rule learning. | IV | CO-4 |
| 4 D- 8 | Discuss the trade-off between exploration and exploitation in reinforcement learning. How does this impact learning efficiency? | IV | CO-4 |
| 4 D-9 | Evaluate the advantages and disadvantages of Q-learning compared to Temporal Difference Learning. | V | CO-4 |
| 4 D-10 | Discuss the effectiveness of inverting resolution in rule learning. Under what conditions does it work best? | V | CO-4 |
| 4 D-11 | Design a hybrid learning algorithm that combines Genetic Algorithms and Reinforcement Learning. Explain how they complement each other. | VI | CO-4 |
| 4 D-12 | Propose an improvement to parallelizing Genetic Algorithms using a new communication strategy between subpopulations. | VI | CO-4 |
| 4 D-13 | Explain how models of evolution and learning relate to reinforcement learning strategies. | II | CO-4 |
| 4 D-14 | Given a non-deterministic environment, how can a reinforcement learning agent adapt its policy effectively? | III | CO-4 |

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|---|---|---|---|
| 4 D-15 | Critically analyze the role of generalization in reinforcement learning and suggest methods to improve it. | V | CO-4 |

Match the following

| | | BT Level | CO |
|---|---|---|---|
| 4M-1 | A. Selection 1. Introduces diversity into the population<br>B. Crossover 2. Evaluates individuals based on problem-solving ability<br>C. Mutation 3. Creates offspring by combining genetic material<br>D. Fitness Function 4. Chooses individuals for reproduction | I | CO4 |
| 4M-2 | A. Hypothesis Space 1. Technique to learn rules from examples<br>B. Sequential Covering 2. The set of all possible solutions in machine learning<br>C. FOIL Algorithm 3. Learns first-order rules using induction<br>D. Inverting Resolution 4. Used to infer logical representations of knowledge | II | CO4 |
| 4M-3 | A. Q-Learning 1. Balances exploration and exploitation using a probability value<br>B. Temporal Difference Learning 2. Learns the optimal action-value function<br>C. Epsilon-Greedy Policy 3. Updates value estimates based on future rewards<br>D. Dynamic Programming 4. Requires a complete model of the environment | III | CO4 |
| 4M-4 | A. Island Model 1. Uses a single, large evolving population<br>B. Steady-State Model 2. Maintains subpopulations that occasionally exchange individuals<br>C. Generational Model 3. Replaces only a few individuals per iteration<br>D. Elitism 4. Ensures the best solutions are carried over to the next generation | IV | CO4 |
| 4M-5 | A. Exploration-Exploitation Dilemma 1. Using function approximation methods<br>B. Large State Space 2. Using deep reinforcement learning<br>C. Non-Deterministic Rewards 3. Using probability-based action selection<br>D. Slow Convergence 4. Applying experience replay and prioritized sampling | V | CO4 |

| UNIT-V | | | |
|---|---|---|---|
| | Multiple choice Questions | BT Level | Course Outcome |
| 5C-1 | What is the primary goal of **Analytical Learning**?<br>A) Learning from labeled examples<br>B) Using prior knowledge to improve learning efficiency<br>C) Randomly exploring the hypothesis space<br>D) Avoiding the use of domain knowledge | I | CO5 |
| 5C-2 | **Explanation-Based Learning (EBL)** primarily relies on which of the following?<br>A) Statistical generalization<br>B) Perfect domain theories<br>C) Random search strategies<br>D) Neural networks | I | CO5 |
| 5C-3 | What is the role of PROLOG-EBG in explanation-based learning?<br>A) To generate new rules from prior experience<br>B) To classify images based on neural networks<br>C) To perform unsupervised learning<br>D) To replace all domain knowledge with examples | II | CO5 |
| 5C-4 | How does **search control knowledge** benefit learning systems?<br>A) By increasing randomness in search<br>B) By making the search process more efficient<br>C) By eliminating all search efforts<br>D) By avoiding the use of hypotheses | II | CO5 |
| 5C-5 | If an agent **modifies search operators using prior knowledge**, what is it trying to achieve?<br>A) Reduce computational complexity<br>B) Increase randomness in learning<br>C) Make learning independent of domain knowledge<br>D) Avoid using hypotheses | III | CO5 |
| 5C-6 | In inductive learning, hypotheses are typically generated based on:<br>A) Prior domain knowledge<br>B) Statistical patterns in data<br>C) Random rule selection<br>D) Fixed pre-defined rules | III | CO5 |
| 5C-7 | Which of the following **best differentiates inductive and analytical learning**?<br>A) Inductive learning depends on prior knowledge, while analytical learning does not<br>B) Analytical learning relies on perfect domain theories, whereas inductive learning does not<br>C) Inductive learning is deterministic, while analytical learning is probabilistic<br>D) Inductive learning always produces more accurate results | IV | CO5 |
| 5C-8 | In explanation-based learning, **when is a learned rule generalized**?<br>A) When it fits all available data points<br>B) When it is consistent with prior domain knowledge<br>C) When it minimizes computational cost<br>D) When it eliminates all examples | IV | CO5 |
| 5C-9 | What is a major **limitation of explanation-based learning (EBL)**?<br>A) It requires a perfect domain theory<br>B) It cannot generalize beyond training data<br>C) It is too slow for real-world applications<br>D) It does not rely on prior knowledge | V | CO5 |
| 5C-10 | Which of the following best describes a **weakness of inductive learning** compared to analytical learning?<br>A) Inductive learning always requires labeled examples<br>B) Inductive learning never leads to correct results<br>C) Inductive learning cannot handle large datasets<br>D) Inductive learning requires a perfect domain theory | V | CO5 |

| | | | |
|---|---|---|---|
| 5C-11 | A researcher is designing a **hybrid learning model** combining inductive and analytical learning. What should be the **primary goal** of this approach?<br>A) Reduce dependency on labeled training data<br>B) Increase randomness in learning<br>C) Remove prior knowledge from learning<br>D) Avoid generating hypotheses | VI | CO5 |
| 5C-12 | To optimize **inductive-analytical learning**, a system should:<br>A) Learn purely from data without prior knowledge<br>B) Use prior knowledge to initialize the hypothesis space<br>C) Ignore previous domain knowledge<br>D) Avoid generalizing learned rules | VI | CO5 |
| 5C-13 | How does **explanation-based learning (EBL) help in search optimization**?<br>A) By reducing the number of hypotheses considered<br>B) By increasing the complexity of search<br>C) By ignoring domain theories<br>D) By randomly selecting solutions | II | CO5 |
| 5C-14 | In a **robot navigation system**, using prior knowledge to adjust search objectives can help in:<br>A) Finding optimal paths faster<br>B) Avoiding all obstacles<br>C) Eliminating the need for reinforcement learning<br>D) Preventing generalization | III | CO5 |
| 5C-15 | Why might **combining inductive and analytical learning** lead to better learning models?<br>A) It improves generalization and reduces reliance on labeled data<br>B) It eliminates the need for search algorithms<br>C) It prevents the need for hypothesis testing<br>D) It avoids using prior knowledge | V | CO5 |
| | **Fill in the Blanks** | BT Level | Course Outcome |
| 5F-1 | Explanation-Based Learning (EBL) requires a _____ domain theory to correctly generalize knowledge. | I | CO5 |
| 5F-2 | In **PROLOG-EBG**, learning occurs by explaining training examples and then extracting _____ from those explanations. | I | CO5 |
| 5F-3 | In EBL, a learned rule is considered useful if it leads to a _____ search space for future problem-solving. | II | CO5 |
| 5F-4 | **Search control knowledge** is used in EBL to improve the efficiency of _____ | II | CO5 |
| 5F-5 | When using prior knowledge to alter the search objective, the goal is to improve _____ and reduce unnecessary computation | III | CO5 |
| 5F-6 | In analytical learning, modifying search operators using prior knowledge helps the system to avoid _____ solutions. | III | CO5 |
| 5F-7 | A key difference between inductive and analytical learning is that inductive learning depends on _____, whereas analytical learning relies on prior domain knowledge. | IV | CO5 |
| 5F-8 | **Inductive learning** is more suitable when a perfect domain theory is _____ or unavailable. | IV | CO5 |
| 5F-9 | A major limitation of explanation-based learning (EBL) is that it depends heavily on the _____ of its domain knowledge. | V | CO5 |
| 5F-10 | A drawback of using prior knowledge to initialize a hypothesis is the risk of _____, where the system becomes too dependent on existing knowledge. | V | CO5 |
| 5F-11 | A hybrid learning approach combining inductive and analytical learning can reduce the need for _____ examples while improving generalization. | VI | CO5 |

| | | | |
|---|---|---|---|
| 5F-12 | One way to improve **inductive-analytical learning** is by dynamically updating _____ to refine future learning. | VI | CO5 |
| 5F-13 | **Explanation-based learning (EBL)** generalizes specific instances by identifying their _____ structure. | II | CO5 |
| 5F-14 | In a **robot navigation system**, using analytical learning can optimize path selection by leveraging _____ about the environment. | III | CO5 |
| 5F-15 | The advantage of combining inductive and analytical learning is that it allows for both data-driven learning and _____ refinement using prior knowledge. | V | CO5 |

5-MARKSQUESTIONS

| | | | |
|---|---|---|---|
| 5 D-1 | What is **Explanation-Based Learning (EBL)**? Define its key characteristics. | I | CO5 |
| 5 D-2 | What is the role of **PROLOG-EBG** in analytical learning? | I | CO5 |
| 5 D-3 | Explain how **perfect domain theories** are essential in Explanation-Based Learning (EBL). | II | CO5 |
| 5 D-4 | Describe the **process of Explanation-Based Learning** with an example. | II | CO5 |
| 5 D-5 | How does search control knowledge improve the efficiency of learning in an AI system? | III | CO5 |
| 5 D-6 | Provide an example of how prior knowledge can be used to modify search objectives in analytical learning. | III | CO5 |
| 5 D-7 | Compare and contrast inductive learning and analytical learning, highlighting their advantages and limitations. | IV | CO5 |
| 5 D- 8 | Why is it necessary to alter search operators using prior knowledge in analytical learning? | IV | CO5 |
| 5 D-9 | What are the limitations of Explanation-Based Learning (EBL)? Discuss possible ways to overcome them. | V | CO5 |
| 5 D-10 | In what scenarios would inductive learning be more effective than analytical learning? Provide justifications | V | CO5 |
| 5 D-11 | Design a hybrid Inductive-Analytical learning system that utilizes the benefits of both approaches. Explain its working. | VI | CO5 |
| 5 D-12 | How can prior knowledge be used to initialize a hypothesis in a combination of inductive and analytical learning? Provide an example. | VI | CO5 |
| 5 D-13 | Explain how Explanation-Based Learning of search control knowledge helps in problem-solving. | II | CO5 |
| 5 D-14 | Suppose you are designing an AI system for medical diagnosis. How could analytical learning improve its decision-making ability? | III | CO5 |
| 5 D-15 | Evaluate the effectiveness of using prior knowledge in machine learning. What trade-offs are involved? | V | CO5 |

Match the following

| | | | BT Level | CO |
|---|---|---|---|---|
| 5M-1 | Explanation-Based Learning (EBL) | Learning method that generalizes from specific instances using prior domain theories. | I | CO5 |
| | PROLOG-EBG | A logic-based implementation of Explanation-Based Generalization. | | |
| | Search Control Knowledge | Knowledge that helps guide and optimize search efficiency in learning systems. | | |
| | Inductive Learning | A method that generalizes patterns from data without requiring prior domain knowledge. | | |
| | Hypothesis Initialization | Using prior knowledge to define an initial hypothesis in machine learning. | | |
| 5M-2 | Inductive Learning | Learns from large datasets and detects patterns. | II | CO5 |
| | Analytical Learning | Uses prior knowledge to improve learning efficiency. | | |
| | Hybrid Learning | Combines inductive and analytical approaches. | | |
| | Altering Search Objective | Modifies learning goals using prior knowledge. | | |
| | Augmenting Search Operators | Changes search strategies to enhance problem-solving. | | |
| 5M-3 | Medical Diagnosis System | Hybrid (Inductive + Analytical) Learning | III | CO5 |
| | Self-Driving Car Navigation | Explanation-Based Learning (EBL) | | |
| | Spam Email Classification | Inductive Learning | | |
| | Logical Theorem Proving | PROLOG-EBG | | |
| | Chess AI Strategy Improvement | Search Control Knowledge | | |
| 5M-4 | Handles noisy and incomplete data well. | Inductive Learning | IV | CO5 |
| | Uses domain knowledge to improve efficiency. | Analytical Learning | | |
| | Reduces the number of training examples needed. | Hybrid Learning | | |
| | Helps guide learning by improving search control. | Explanation-Based Learning | | |
| | Enhances the effectiveness of learning from experience. | Using Prior Knowledge | | |
| 5M-5 | Requires a perfect domain theory. | Explanation-Based Learning (EBL) | V | CO5 |
| | Computationally expensive with large datasets. | Inductive Learning | | |
| | Can suffer from bias in prior knowledge. | Analytical Learning | | |
| | May be difficult to integrate different approaches. | Hybrid Learning | | |
| | Requires extensive labeled data for good performance. | Inductive Learning | | |

Write Your Ht.No. D4

Subject Code: **R22CSM3112**

# SRI INDU COLLEGE OF ENGINEERING&TECHNOLOGY

(An Autonomous Institution under UGC,NewDelhi.)-Recognized under 2(f)and12(B) of UGC Act 1956.

## III B.Tech-II Semester

**Model Question Paper**

## MACHINE LEARNING(R22CSM3112)

**(Common to AIDS-A&B)**

**Duration: 3Hrs** **Maximum Marks:60 M**

## *SECTION-A*

***Answer all the following questions.***

***1*)** **(10Qx1M=10 M)**

a. Define machine learning.
b. What is Decision Tree in ml?
c. What is perception.?
d. What is hypothesis?
e. What is Baye's theorem in ml?
f. Define computational learning?
g. Define genetic algorithm?
h. What is reinforcement learning in ml?
i. What is analytical learning?
j. What is prior knowledge?

# SECTION–B

***Answer FIVE questions choosing atleast one from each unit*** **(5Qx10M=50M)**

## UNIT-I

3) Explain the concept learning. Describe the Find-S algorithm and the Candidate Elimination Algorithm.

(OR)

Discuss decision tree learning. How is the hypothesis space searched in decision tree learning?

## UNIT-II

Explain multilayer network and backpropagation algorithm with example.

(OR)

Discuss difference in error of two hypotheses, comparing learning algorithms.

## UNIT-III

DISCUSS Naïve Bayes classifier for text classification.

(OR)

Discuss k-nearest neighbour algorithm with example.

## UNIT-IV

Explain the Genetic algorithms with an illustrative example.

(OR)

Explain Reinforcement Learning and the learning task and Q–learning?

## UNIT-V

Briefly explain learning with perfect domain theories: PROLOG-EBG, remarks on explanation-based learning.

(OR)

Discuss Combining Inductive and Analytical Learning-Motivation and inductive-analytical approaches?

SRI INDU COLLEGE OF ENGINEERING&TECHNOLOGY

D4

**III-B.Tech-IISemester–Model Mid Question Paper**

**(R22CSM3112)MACHINE LEARNING**

**(Common to AIDS)**

**Duration:90Mins** **MaxMarks:25M**

**Section–A**

**Answer *All* the questions** **Marks:=10M**

**MCQ'S --FILL IN BLANKS-- MATCH THE FOLLOWING**

**Section–B**

**Answer any *FOUR* questions** **Marks:4Qx5M=20M**