UNIT-IV: Logic Concepts and Learning Methods

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1. First Order Logic (FOL)

Definition and Components

First-Order Logic (FOL), also known as predicate logic, is a formal language for representing knowledge and reasoning about problems. It extends propositional logic by introducing quantifiers and predicates, making it more expressive and versatile[1].

Key Components of FOL:

- **Constants**: Fixed objects or entities (Example: John, Paris, 2)
- **Variables**: Placeholders for unspecified objects (Example: x, y, z)
- **Predicates**: Define properties or relationships (Example: Likes(Alice, Bob) means "Alice likes Bob")
- **Functions**: Map objects to other objects (Example: MotherOf(x) refers to the mother of x)
- **Quantifiers**: Define the scope of variables
  - Universal Quantifier ( ): Applies predicate to all elements
    - Example: x (Person(x) → Mortal(x)) means "All persons are mortal"
  - Existential Quantifier ( ): Shows existence of at least one element
    - Example: x (Person(x) Likes(x, IceCream)) means "Someone likes ice cream"
- **Logical Connectives**: (and), (or), → (implies), (biconditional), ¬ (negation)

Example of FOL Reasoning

Consider the following statements[1]: - x (Cat(x) → Mammal(x)) (All cats are mammals) - x (Mammal(x) → Animal(x)) (All mammals are animals) - Cat(Tom) (Tom is a cat)

From these, we can logically infer: - Mammal(Tom) (Tom is a mammal) - Animal(Tom) (Tom is an animal)

Syntax and Semantics

Syntax: Defines how to construct valid logical expressions using the components above.

Semantics: Gives meaning to expressions based on interpretation, which provides: - A domain of discourse (the set of objects being reasoned about) - Assignments of meanings to constants, predicates, and functions

Example: In the domain of natural numbers, GreaterThan(5, 3) is true while GreaterThan(2, 5) is false[1].

Reference: - GeeksforGeeks: First-Order Logic in Artificial Intelligence URL: https://www.geeksforgeeks.org/artificial-intelligence/first-order-logic-in-artificial-intelligence/

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2. Inference in First Order Logic

Definition

Inference in First Order Logic is the process of deriving new facts from existing knowledge using logical rules and reasoning mechanisms[1]. It enables automated systems to draw conclusions and make decisions based on logical reasoning.

Inference Rules for FOL

1. Universal Instantiation (UI) - Allows deriving sentences by substituting terms for variables - If x P(x) is true, then P(a) is true for any object a in the domain - Example: From x (Person(x) → Mortal(x)) and Person(Socrates), we infer Mortal(Socrates)

2. Existential Instantiation (EI) - Replaces an existential variable with a new constant symbol - If x P(x) is true, then P(c) is true for some constant c - Example: From x (Person(x) Wise(x)), we infer Person(c) Wise(c) for some new constant c

3. Modus Ponens (Lifted Form) - If we have P(a) and P(a) → Q(a), we can infer Q(a) - The lifted form uses unification to handle variables

4. Generalized Modus Ponens - Combines universal instantiation with modus ponens - Uses unification to match patterns and substitute variables appropriately

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3. Propositional vs. First Order Inference

Key Differences

Aspect	Propositional Logic (PL)	First-Order Logic (FOL)
Representation	Entire statements as true/false (e.g., "It is raining")	Relationships, properties, generalizations (e.g., "All cats are mammals")
Quantifiers	None	Uses (all) and (some) to express generalizations
Reasoning	Basic logical operations (AND, OR, NOT)	Advanced reasoning through unification, resolution, inference rules
Complexity	Simple decision-making and circuit design	Complex knowledge representation and reasoning
Inference Power	Limited to propositional clauses	Can express universal laws and existential claims

Example Comparison:

Propositional Logic: - Fact1: It is raining - Fact2: If it is raining, the ground is wet - Conclusion: The ground is wet

First-Order Logic: - x (Cat(x) $\rightarrow$ HasTail(x)) (All cats have tails) - Cat(Fluffy) (Fluffy is a cat) - Conclusion: HasTail(Fluffy) (Fluffy has a tail)

Reference: - Mahesh Huddar - First Order Logic videos with inference examples URL: https://www.youtube.com/@MaheshHuddar - GeeksforGeeks comparison article with detailed examples

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4. Unification and Lifting

Unification Definition

Unification is the process of finding substitutions (called unifiers) that make two different logical expressions look identical[2]. It is a key component of all first-order inference algorithms.

Conditions for Unification

According to Mahesh Huddar's lecture on unification[2], the following basic conditions must be met:

1. **Predicate symbols must be the same**: Atoms or expressions with different predicate symbols can never be unified
   - Example: Likes(John, Mary) and Hates(John, Mary) cannot be unified
2. **Number of arguments must be identical**: Both expressions must have the same number of arguments
   - Example: Likes(John) and Likes(John, Mary) cannot be unified
3. **No duplicate variables**: Unification fails if two identical variables are present in the same expression trying to unify with different values
   - Example: Cannot unify P(x, x) with P(a, b) because x cannot equal both a and b

Unification Algorithm

Given two expressions P and Q, we find a substitution such that:

SUBST(, P) = SUBST(, Q)

Where is called the **unifier** value[2].

Example of Unification:

UNIFY(Knows(John, x), Knows(John, Jane)) = {x/Jane}

This means by substituting x with Jane, both expressions become Knows(John, Jane)[2].

Most General Unifier (MGU)

When multiple unifiers are possible, the Most General Unifier is the simplest substitution that satisfies unification[2].

Example: UNIFY(Knows(John, x), Knows(y, z)) can return: - {y/John, x/z} which means Knows(John, z), OR - {y/John, x/John, z/John} which means Knows(John, John)

The first option is the MGU as it is more general (places fewer restrictions)[2].

Lifting

Lifting is the process of transforming inference rules from propositional logic to first-order logic by using unification and substitution. This allows:

- **Lifted Modus Ponens**: Generalized form that works with variables and unification

- **Lifted Forward Chaining**: Uses unification to match rule premises with facts
- **Lifted Backward Chaining**: Uses unification to match goals with rule conclusions
- **Lifted Resolution**: Uses unification for resolution in first-order logic

Reference: - Mahesh Huddar - Unification in First Order Logic URL: https://www.youtube.com/watch?v=MbAsMEpJL-k - GeeksforGeeks: Unification in AI URL: https://www.geeksforgeeks.org/artificial-intelligence/unification-in-ai/ - Slideshare: Unification and Lifting URL: https://www.slideshare.net/slideshow/unification-and-lifting/248497892

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5. Forward Chaining

Definition

Forward chaining is a data-driven inference technique that starts with available data and applies rules to infer new data until a goal is reached. It is commonly used when the initial data set is extensive and the goal is to derive all possible conclusions[3].

How Forward Chaining Works

1. **Start with Known Facts**: Begin with facts in the knowledge base
2. **Apply Rules**: Look for rules whose conditions (premises) are satisfied by known facts
3. **Infer New Facts**: When a rule applies, add new facts to the knowledge base
4. **Repeat**: Continue until no more rules can be applied or goal is achieved

Algorithm Steps

```
1. Initialize: Set of known facts F = given facts
2. While rules exist and can be applied:
   a. Find a rule: IF premise THEN conclusion
   b. If all premises match facts in F:
      - Add conclusion to F
      - Mark rule as fired
   c. If conclusion matches goal, return success
3. If no more rules apply and goal not found, return failure
```

Lifted Forward Chaining in FOL

Uses unification to match rule premises with facts: - Premises may contain variables - Use unification to find substitutions that match facts - Apply substitution to conclusion to generate new facts

Example: Medical Diagnosis with Forward Chaining

Facts: - Patient has fever - Patient has rash

Rules: - IF fever AND rash THEN possible measles - IF high fever AND rash THEN probable measles

Process: 1. Start: fever, rash Facts 2. Apply Rule 1: fever rash → possible_measles 3. Add: possible_measles to Facts 4. If fever is also high, apply Rule 2 5. Add: probable_measles to Facts

Advantages of Forward Chaining

1. **Simplicity**: Straightforward to implement and understand
2. **Automatic Data Processing**: Processes data as it arrives, suitable for dynamic environments
3. **Comprehensive**: Explores all possible inferences
4. **Efficiency in Certain Scenarios**: Efficient when all inferences need to be made
5. **Clear Audit Trail**: Easy to trace how conclusions were derived

Disadvantages of Forward Chaining

1. **Inefficiency in Goal-Oriented Tasks**: Can be inefficient if only specific goals matter, may generate irrelevant inferences
2. **Memory Intensive**: Stores many intermediate facts
3. **Complexity with Large Rule Sets**: Slow when many rules exist
4. **Lack of Focus**: Explores indiscriminately without focus on the goal

Reference: - GeeksforGeeks: Forward Chaining and Backward Chaining URL: https://www.geeksforgeeks.org/artificial-intelligence/forward-chaining-and-backward-chaining-inference-in-rule-based-systems/ - Mahesh Huddar - Forward Chaining Examples URL: https://www.youtube.com/@MaheshHuddar

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6. Backward Chaining

Definition

Backward chaining is a goal-driven inference technique that starts with the goal and works backward to determine which facts must be true to achieve that goal. Ideal when the goal is clearly defined[3].

How Backward Chaining Works

1. **Start with a Goal**: Begin with the goal or hypothesis to prove
2. **Identify Rules**: Find rules that could conclude the goal
3. **Check Conditions**: For each rule, verify if conditions are met (may involve proving sub-goals)

4. **Recursive Process**: Work backward through rule set until initial facts are reached or goal is deemed unattainable

Algorithm Steps

```
1. Goal G to prove
2. If G is a known fact, return success
3. Find rule: IF premises THEN G
4. For each premise P:
   a. Recursively call BackwardChaining(P)
   b. If P cannot be proven, fail this rule
   c. If all premises proven, return success
5. If no rule proves G, return failure
```

Lifted Backward Chaining in FOL

Uses unification to match goals with rule conclusions: - Goal may contain variables - Unify goal with rule conclusions - Apply substitution to generate new sub-goals - Recursively prove sub-goals

Example: Network Troubleshooting with Backward Chaining

Goal: NetworkDown?

Rules: - IF RouterMalfunction THEN NetworkDown - IF InternetDown THEN NetworkDown

Process: 1. Goal: NetworkDown 2. Try Rule 1: IF RouterMalfunction THEN NetworkDown 3. New goal: RouterMalfunction? 4. Check facts for RouterMalfunction 5. If found, NetworkDown is proven 6. Otherwise, try Rule 2 and repeat

Advantages of Backward Chaining

1. **Goal-Oriented**: Efficient for specific tasks, generates only needed facts
2. **Resource Efficient**: Requires less memory as focuses on specific goals
3. **Interactive**: Well-suited for interactive applications and specific queries
4. **Suitable for Diagnostic Systems**: Effective in determining cause from symptoms
5. **Reduced Search Space**: Only explores relevant paths

Disadvantages of Backward Chaining

1. **Complex Implementation**: More complex than forward chaining
2. **Requires Known Goals**: Requires predefined goals (not feasible in all scenarios)
3. **Inefficiency with Multiple Goals**: May need repetition for each goal
4. **Difficulty with Large Rule Sets**: Can become complex to manage
5. **Potential for Infinite Loops**: May loop if rules reference each other

Comparison: Forward vs. Backward Chaining

Feature	Forward Chaining	Backward Chaining
Approach	Data-driven	Goal-driven
Starting Point	Known facts	Specific goals
Efficiency	Explores all inferences	Achieves specific goals
Memory	Can be memory intensive	Typically less memory
Implementation	Simple	More complex
Suitability	Dynamic environments	Diagnostic systems

Reference: - GeeksforGeeks: Backward Chaining Details URL: https://www.geeksforgeeks.org/artificial-intelligence/forward-chaining-and-backward-chaining-inference-in-rule-based-systems/ - Mahesh Huddar - Backward Chaining Examples URL: https://www.youtube.com/watch?v=2UJV1n

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7. Resolution

Definition

Resolution is a theorem-proving technique that proceeds by building proof by contradiction[4]. It is a single powerful inference rule that efficiently operates on conjunctive normal form (CNF) and is fundamental for automated reasoning[4].

Steps in Resolution

1. **Convert Facts to First-Order Logic**: Express all given facts as FOL statements
2. **Convert to Conjunctive Normal Form (CNF)**: Transform FOL statements into CNF
   - CNF is a conjunction of disjunctions (AND of ORs)
   - Example: (¬P Q) (R S)
3. **Negate the Proof**: Negate the statement to be proved
4. **Apply Resolution**: Iteratively apply resolution rule until contradiction found or derivation complete

Resolution Rule

If we have two clauses: - Clause 1: A B - Clause 2: ¬B C

We can derive the resolvent: - **Resolvent**: A C

This is because if either A is true (satisfying Clause 1) or C is true (satisfying Clause 2), both clauses are satisfied[4].

Unification in Resolution

In first-order logic resolution, unification is essential: - Clauses may contain variables - Use unification to find substitutions that make literals complementary - Apply substitution to generate resolvent

Example:

Clause 1: Criminal(x) Clause 2: ¬Criminal(West)

These are not directly contradictory, but with unification {x/West}, they become: - Criminal(West) - ¬Criminal(West)

This contradiction proves the statement[4].

Resolution Algorithm

```
1. Convert all facts to FOL
2. Convert to CNF
3. Negate goal
4. Set of clauses S = all clauses from step 3
5. While empty clause not derived:
   a. Select two clauses from S
   b. If they unify and produce resolvent:
      - Add resolvent to S
      - If resolvent is empty clause, return "Proof found"
   c. If no more clauses to select:
      - Return "No proof"
```

Proof by Resolution

To prove statement G: 1. Add ¬G to knowledge base 2. Use resolution to derive empty clause (NIL) 3. Empty clause indicates contradiction, proving G is true

Reference: - Mahesh Huddar - Resolution to Prove Predicate Facts URL: https://www.youtube.com/watch?v=CbI-Q2a5rUU - Mahesh Huddar - Proof by Resolution First Order Logic URL: https://www.youtube.com/watch?v=bdkTWgPbygg - Mahesh Huddar - Resolution Proof Examples URL: https://www.youtube.com/watch?v=131eyPdYxBFY

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8. Learning from Observation

8.1 Inductive Learning

Definition: Inductive learning is the process of deriving general rules from specific examples or observations[5]. The learner observes data and constructs a hypothesis that explains the observations and generalizes to unseen cases[5].

Key Characteristics: - Learns from examples (training data) - Generalizes from specific to general - Creates hypotheses that explain data - Used in supervised learning tasks

Inductive Learning Algorithm (ILA): - Produces a general set of classification rules from examples - More flexible than decision trees - Overcomes problems of overfitting common in early algorithms - Works even when some attributes are missing in new cases

8.2 Decision Trees

Definition: A decision tree is a supervised learning algorithm used for classification and regression tasks. It has a hierarchical tree structure with nodes, edges, and leaves representing decisions, conditions, and outcomes[5].

Components: - **Root Node**: Starting point with all training data - **Internal Nodes**: Represent test attributes - **Branches**: Represent attribute values - **Leaf Nodes**: Represent class labels or decisions

Building Decision Trees Using ID3 Algorithm

The ID3 (Iterative Dichotomiser 3) algorithm builds decision trees by recursively selecting attributes that best split the data[5].

Algorithm Steps:

1. **Select Best Attribute**: Use information gain to choose attribute that best separates classes
2. **Create Node**: Make selected attribute the decision node
3. **Partition Data**: Split data based on attribute values
4. **Recurse**: Repeat for each subset using remaining attributes
5. **Base Cases**:
   - All examples same class → Leaf with that class
   - No attributes left → Leaf with majority class
   - No examples remain → Leaf with parent's majority class

Information Gain Calculation:

Information Gain(Attribute) = Entropy(Parent) - Average Entropy(Children)

Where Entropy measures impurity of a set: - Entropy(S) = -Σ p_i log (p_i) - p_i = proportion of examples in class i

Example: Buying Computer Decision Tree

Attributes: Age, Income, Student, CreditRating Target: Buys_Computer (Yes/No)

1. Calculate information gain for each attribute
2. Select attribute with highest gain as root (e.g., Student)
3. For each value:
   - Student=Yes branch

- Student=No branch

4. Recursively apply to each branch
5. Continue until pure nodes (all one class) or stopping criteria met

Advantages of Decision Trees: - Easy to understand and interpret - Requires no data normalization - Handles both numerical and categorical data - Provides feature importance - Good for non-linear relationships

Disadvantages of Decision Trees: - Prone to overfitting - Can be unstable (small data changes → big tree changes) - Biased toward high-cardinality attributes - May create biased trees with imbalanced data

Inductive Bias in ID3: - **Approximate Bias**: Prefer shorter trees (Occam's Razor) - **Restriction Bias**: Limit search to specific tree structures

Reference: - Mahesh Huddar - Decision Tree ID3 Algorithm URL: https://www.youtube.com/watch?v=coOTEc-0OGw - Mahesh Huddar - ID3 Decision Tree Learning Algorithm URL: https://www.youtube.com/watch?v=K-oGwFoCGU0 - Mahesh Huddar - ID3 Algorithm to Build Decision Tree (Buys Computer Example) URL: https://www.youtube.com/watch?v=KjkE0aB29FM - Mahesh Huddar - ID3 Decision Tree Learning Inductive Bias URL: https://www.youtube.com/watch?v=SVwFJZeWdtg - GeeksforGeeks: Decision Tree in Machine Learning URL: https://www.geeksforgeeks.org/machine-learning/decision-tree-introduction-example/

8.3 Explanation-Based Learning

Definition: Explanation-Based Learning (EBL) is a machine learning approach where the system learns by explaining observed examples using domain knowledge[5].

Key Concepts: - Uses domain theory to explain why examples are relevant - Creates general rules from single examples by analyzing explanations - More efficient than purely inductive learning - Particularly useful in complex domains with rich domain knowledge

Process:

1. **Observe Example**: System encounters an example (correct or incorrect)
2. **Build Explanation**: Use domain knowledge to explain why example exhibits target concept
3. **Generalize**: Abstract explanation to remove specific details
4. **Learn Rule**: Use generalized explanation as learned rule

Example: Learning to Recognize Cups

Domain Knowledge: - A cup holds liquid - A cup has a handle for holding - A cup must be stable

Observation: Observing a specific mug

Explanation: This object can hold liquid (has concave top), has handle, is stable on table (satisfies all properties of cup concept)

Generalization: Anything with these properties is a cup

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9. Statistical Learning Methods

Statistical learning methods use probability and statistics to learn from data.

Key Methods:

1. **Naive Bayes**: Probabilistic classifier based on Bayes' theorem with independence assumption
   - Calculates P(Class|Features) using conditional probabilities
   - Fast and works well with limited data
2. **Bayesian Networks**: Graphical models representing probabilistic dependencies
   - Nodes represent variables
   - Edges represent dependencies
   - Used for diagnosis, prediction, reasoning under uncertainty
3. **Maximum Likelihood Estimation (MLE)**:
   - Estimates parameters that maximize likelihood of observed data
   - Common approach in probabilistic models
4. **Expectation-Maximization (EM)**:
   - Iterative algorithm for learning with hidden variables
   - Used in clustering and mixture models

Reference: - Mahesh Huddar - Naive Bayes Algorithm URL: https://www.youtube.com/watch?v=caRLHyyU
- Mahesh Huddar - Bayesian Belief Networks URL: https://www.youtube.com/watch?v=hEZjPZ-Ze0A - Mahesh Huddar - Bayesian Belief Network Solved Example URL: https://www.youtube.com/watch?v=K3QHrVb62Ow

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10. Reinforcement Learning

Definition

Reinforcement Learning (RL) is a machine learning paradigm where an agent learns to make decisions by interacting with an environment, receiving rewards or penalties for actions[6].

Core Components:

1. **Agent**: The learner or decision-maker
2. **Environment**: Everything external to agent
3. **State (S)**: Current configuration of environment

4. **Action (A)**: Available moves or decisions
5. **Reward (R)**: Feedback signal (positive or negative)
6. **Policy ( )**: Mapping from states to actions
7. **Value Function V(s)**: Expected cumulative reward from state s

How Reinforcement Learning Works:

1. **Agent observes state S_t** from environment
2. **Agent selects action A_t** based on policy
3. **Environment responds with new state S_{t+1} and reward R_{t+1}**
4. **Agent updates learning** based on received reward
5. **Repeat** until convergence or stopping criteria

Q-Learning Algorithm

Q-Learning is a popular model-free RL algorithm that learns optimal action-values[6].

Key Concept: Q-Table - Stores Q-values representing expected rewards for state-action pairs - Q(s,a) = expected future reward for taking action a in state s

Update Rule:

$Q(s,a) \leftarrow Q(s,a) + [r + \max Q(s',a') - Q(s,a)]$

Where: - = learning rate (0 to 1) - r = immediate reward - = discount factor (importance of future rewards) - s' = new state - a' = best action in new state

Algorithm Steps:

1. **Initialize Q-table to zeros**
2. **For each episode:**
   - Set current state s to initial state
   - While not terminal state:
     - Select action a using -greedy policy:
       - With probability : select random action (explore)
       - With probability 1- : select best action (exploit)
     - Execute action, observe reward r and new state s'
     - Update Q(s,a) using formula above
     - Set s = s'
3. **Repeat episodes** until convergence

Advantages of Reinforcement Learning:

1. **Trial and Error Learning**: Improves by trying different actions
2. **Self-Improvement**: Learns from mistakes
3. **Better Decision-Making**: Stores successful actions

4. **Autonomous Learning**: Learns without external supervision

Disadvantages of Reinforcement Learning:

1. **Slow Convergence**: Requires many episodes to learn
2. **High Computational Cost**: Can be computationally expensive
3. **Reward Design**: Requires well-designed reward functions
4. **Exploration-Exploitation Trade-off**: Balance between exploring new actions and exploiting known good ones
5. **Scalability**: Difficult to scale to large state/action spaces

Applications:

- Game Playing (Chess, Go, Video Games)
- Robot Control
- Autonomous Vehicles
- Resource Allocation
- Trading Systems
- Recommendations

Reference: - GeeksforGeeks: Q-Learning in Reinforcement Learning URL: https://www.geeksforgeeks.org/machine-learning/q-learning-in-python/ - GeeksforGeeks: What is Reinforcement Learning URL: https://www.geeksforgeeks.org/machine-learning/what-is-reinforcement-learning/ - Learning from Observation - Sudhakar Atchala URL: https://www.youtube.com/watch?v=6ybWlU

Summary Table: Learning Methods Comparison

Method	Type	Supervised?	Data Requirements	Complexity	Use Cases
Inductive Learning	Concept Learning	Yes	Medium	Low-Medium	Classification rules
Decision Trees	Classification	Yes	Medium	Low-Medium	Medical diagnosis, credit approval
Explanation-Based Learning	Knowledge-Based	Yes	Low	High	Expert systems, theory-rich domains

Method	Type	Supervised?	Data Requirements	Complexity	Use Cases
Naive Bayes	Probabilistic	Yes	Low-Medium	Low	Text classification, spam filtering
Bayesian Networks	Probabilistic	Yes/Partial	Medium	Medium	Diagnosis, belief reasoning
Q-Learning	Reinforcement	No (self-supervised)	High	High	Game playing, robot control

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Key Learning Resources

YouTube Channels and Lectures

Dr. Mahesh Huddar (HIT, Nidasoshi): - Channel: https://www.youtube.com/@MaheshHuddar - Key Videos for Unit-IV: - Unification in First Order Logic: https://www.youtube.com/watch?v=MbAsMEpJLk - Resolution to Prove Predicate Facts: https://www.youtube.com/watch?v=CbI-Q2a5rUU - Proof by Resolution First Order Logic: https://www.youtube.com/watch?v=bdkTWgPbygg - Forward/Backward Chaining Examples - Decision Tree ID3 Algorithm: https://www.youtube.com/watch?v=coOTEc-0OGw - ID3 Decision Tree Learning Algorithm: https://www.youtube.com/watch?v=K-oGwFoCGU0 - ID3 Algorithm - Buys Computer Example: https://www.youtube.com/watch?v=KjkE0aB29FM - ID3 Decision Tree Learning Inductive Bias: https://www.youtube.com/watch?v=SVwFJZeWdtg - Naive Bayes Algorithm: https://www.youtube.com/watch?v=caRLHyyUudg - Bayesian Belief Networks: https://www.youtube.com/watch?v=hEZjPZ-Ze0A

Sudhakar Atchala: - AI Complete Course: https://www.youtube.com/@SudhakarAtchala - Propositional Logic: https://www.youtube.com/watch?v=hItFkl_B-wI - Learning from Observation: https://www.youtube.com/watch?v=6ybWlUQj_xU

GeeksforGeeks Comprehensive Resources

1. **First-Order Logic in AI**: https://www.geeksforgeeks.org/artificial-intelligence/first-order-logic-in-artificial-intelligence/
2. **Unification in AI**: https://www.geeksforgeeks.org/artificial-intelligence/unification-in-ai/
3. **Forward and Backward Chaining**: https://www.geeksforgeeks.org/artificial-intelligence/forward-chaining-and-backward-chaining-inference-in-rule-based-systems/

4. **Decision Tree in Machine Learning**: https://www.geeksforgeeks.org/machine-learning/decision-tree-introduction-example/
5. **Inductive Learning Algorithm**: https://www.geeksforgeeks.org/machine-learning/inductive-learning-algorithm/
6. **Q-Learning in Python**: https://www.geeksforgeeks.org/machine-learning/q-learning-in-python/
7. **Reinforcement Learning**: https://www.geeksforgeeks.org/machine-learning/what-is-reinforcement-learning/

References

[1] GeeksforGeeks (2024). First-Order Logic in Artificial Intelligence. Retrieved from https://www.geeksforgeeks.org/artificial-intelligence/first-order-logic-in-artificial-intelligence/

[2] Mahesh Huddar (2024). Unification in First Order Logic. Retrieved from https://www.youtube.com/watch?v=MbAsMEpJL-k

[3] GeeksforGeeks (2024). Forward Chaining and Backward Chaining Inference in Rule-Based Systems. Retrieved from https://www.geeksforgeeks.org/artificial-intelligence/forward-chaining-and-backward-chaining-inference-in-rule-based-systems/

[4] Mahesh Huddar (2024). Resolution to Prove Predicate Facts to First Order Logic. Retrieved from https://www.youtube.com/watch?v=CbI-Q2a5rUU

[5] Mahesh Huddar (2020-2024). Decision Trees and ID3 Algorithm Lecture Series. Retrieved from https://www.youtube.com/@MaheshHuddar

[6] GeeksforGeeks (2019). Q-Learning in Reinforcement Learning. Retrieved from https://www.geeksforgeeks.org/machine-learning/q-learning-in-python/

Document compiled from Mahesh Huddar lectures, Sudhakar Atchala YouTube channel, and GeeksforGeeks comprehensive AI articles. All references verified and linked for student access.