# UNIT 1

## 1. Discuss Artificial Intelligence (AI) and explain its main goals.

**Definition of AI:**

Artificial Intelligence is defined as "*the study of how to make computers do things at which, at the moment, people are better.*" It is also described as "*the ability of a computer to act like a human being.*"

AI systems aim to create agent programs that perform well in a given environment for a given architecture.

**It differs from natural intelligence in that:**

- It is programmed by humans (not hereditary).
- Requires knowledge base (KB) + electricity to generate output.
- AI systems / expert systems can aggregate many people's experience and ideas.

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### Main Goals of AI

The goals are often described under four major approaches (Fig. 1.1 in PDF):

1. **Systems that Think Like Humans** (*Cognitive Modelling Approach*)
   - Understand and model human thought processes.
   - Uses cognitive science (psychology + AI models) to create systems that simulate human cognition.
2. **Systems that Act Like Humans** (*Turing Test Approach*)
   - Proposed by Alan Turing (1950).
   - If a human interrogator cannot distinguish the machine's responses from a human's, it passes.
   - Requires:
     - Natural Language Processing
     - Knowledge Representation
     - Automated Reasoning
     - Machine Learning
   - *Total Turing Test* additionally needs computer vision and robotics.
3. **Systems that Think Rationally** (*Laws of Thought Approach*)
   - Based on Aristotle's principles of correct reasoning (syllogisms).
   - Derive logically valid conclusions from correct premises.
   - Example:
     "Socrates is a man; all men are mortal; therefore Socrates is mortal."
4. **Systems that Act Rationally** (*Rational Agent Approach*)
   - Focus on doing the **right thing** to maximize goal achievement, given available information.
   - Action may be reflexive (like blinking) if it serves the goal.
   - Emphasis on decision-making for optimal performance, not necessarily human-like thought.

## 2. Describe the early work in AI and mention key milestones in its development.

Here is the enhanced answer for "2. Describe the early work in AI and mention key milestones in its development," with 2 to 3 lines of theory added to each point for clarity:

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### Early Work in AI

1. **Aristotle's "Laws of Thought" (4th century BC)**
   Aristotle formalized the basis of logical reasoning through syllogisms, providing a structured way to derive conclusions from premises. This laid the intellectual groundwork for symbolic logic, which is fundamental in AI for representing and reasoning with knowledge.
2. **Formal Logic & Reasoning Systems**
   The development of formal logic enabled machines to manipulate symbols and perform deductive reasoning. This approach underpins early AI systems that emulate human thought processes by following strict logical rules.
3. **Alan Turing (1950) – Turing Test**
   Alan Turing proposed the Turing Test as a practical way to define machine intelligence based on indistinguishable

communication from humans. This spurred AI research to focus on natural language processing and human-like interaction.

4. **Cognitive Modelling Approach**
   This approach aimed to replicate human thought processes by integrating psychology and AI models, allowing the simulation of human cognition for vision, reasoning, and learning. It represents an early attempt to understand how intelligence operates practically.

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**Key Milestones in AI Development**

1. **1950s–1960s: Early AI Programs**
   Pioneering AI research produced game-playing software and search algorithms that explored problem spaces systematically. These developments demonstrated computers could perform complex intellectual tasks under programmed guidance.
2. **1956 – Dartmouth Workshop**
   The Dartmouth Workshop officially established AI as a research field, bringing together experts to explore how machines could simulate intelligence. It marked the beginning of AI as a distinct scientific discipline.
3. **Expert Systems (1970s–1980s)**
   Expert systems aggregated human domain knowledge into computerized rules, enabling automated decision-making and problem-solving in specialized areas like medical diagnosis. They showcased AI's practical applications in knowledge representation and inference.
4. **The Total Turing Test**
   Extending the original test, this milestone incorporated sensory perception (computer vision) and physical interaction (robotics), pushing AI toward creating agents capable of perceiving and manipulating the real world as humans do.
5. **Integration with Robotics & Perception**
   Combining AI with robotics and perception technologies allowed autonomous agents to interact dynamically with complex environments. This milestone was crucial in advancing intelligent systems that operate beyond purely virtual tasks.

### 3. Explain task domains of an AI system. Give examples for each domain.

Here is the enhanced version of the answer for "4. Illustrate task domains of an AI system. Give examples for each domain," with 2 to 3 lines of theory added for each point:

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**Task Domains of an AI System with Examples and Explanation**

1. **Route-Finding Problems**
   AI systems in this domain solve problems related to determining optimal paths or routes between locations. Such problems require searching through a network of interconnected nodes and edges to minimize cost, time, or distance.
   **Example:** Computer network routing directs data packets efficiently; military operations use route planning for strategic troop movements; airline travel systems optimize flight paths and schedules.
2. **Touring Problems**
   This domain involves visiting multiple locations with specific constraints, such as visiting each location at least once. AI tackles complexity by searching through permutations of locations to optimize travel. These problems model real logistic and planning challenges in transportation and manufacturing.
   **Example:** The Traveling Salesperson Problem (TSP) demands visiting each city exactly once with minimal travel cost, applied in circuit board drilling and warehouse stocking.
3. **Robot Navigation**
   Robot navigation involves guiding robots through continuous and dynamic environments, accounting for sensory inputs and physical constraints. It requires real-time decision-making and path planning over potentially infinite states and actions.

**Example:** Autonomous vehicles navigating roads safely; industrial robots moving components along assembly lines; delivery drones finding navigation paths in complex spaces.

4. **Very-Large-Scale Integration (VLSI) Layout**
   AI aids in positioning millions of electronic components on semiconductor chips, optimizing for minimal area, delay, and interference. This involves solving large combinatorial optimization problems that affect chip performance and manufacturing yield.
   **Example:** Cell layout design and channel routing on silicon chips use AI to reduce delays and energy consumption.
5. **Automatic Assembly Sequencing**
   In complex manufacturing, the order of assembling parts is critical to efficiency and feasibility. AI plans assembly sequences to avoid rework and optimize workflows. This domain also extends to bioinformatics for molecular design tasks.
   **Example:** Assembly of electric motors requires sequencing to ensure parts fit correctly; protein design uses AI to find amino acid sequences that fold into functional proteins.
6. **Internet Searching**
   AI techniques enable effective retrieval and ranking of information from the vast and unstructured data on the internet. Search algorithms model the web as a graph to navigate and extract relevant content, improving accessibility and user experience.
   **Example:** Web crawlers indexing pages, search engines delivering relevant results, and shopping deal finders scanning online catalogs.

## 4. Differentiate between toy problems and real-world problems in AI problem representation.

| **Aspect** | **Toy Problems** | **Real-World Problems** |
|---|---|---|
| **Purpose** | Used to illustrate AI concepts, test and compare algorithms in a controlled, simplified setting. | Aim to solve practical problems that have real-world utility and impact. |
| **Complexity** | Simple, well-defined with limited variables; easy to model and solve. | Highly complex with numerous variables, constraints, and uncertainty. |
| **State Space** | Small or moderate, often finite; allows exhaustive search. | Very large, possibly infinite; requires heuristics and approximations to solve. |
| **Observability & Control** | Fully observable and deterministic environments are common. | Often partially observable and stochastic with unpredictable dynamics. |
| **Resources Required** | Minimal computational power; solvable within short time and memory limits. | Requires significant computation, storage, and time to handle large datasets and real-time responses. |
| **Solution Usefulness** | Primarily academic/educational to demonstrate techniques. | Directly useful to industries, services, and everyday applications. |
| **Model Accuracy** | Abstract models with perfect information and no noise. | Real-world models often incomplete, noisy, and approximate due to imperfect data. |
| **Testing & Evaluation** | Easy to reproduce and compare across researchers. | Testing can be costly, time-consuming, and environment-dependent. |
| **Examples** | Vacuum World, 8-Puzzle, 8-Queens Problem. | Route finding in maps, airline scheduling, robot navigation, VLSI layout. |

# UNIT 2

## 5. Discuss Breadth-First Search (BFS) with its algorithm and complexity.

### What is Breadth-First Search (BFS)?

Breadth-First Search (BFS) is an uninformed search strategy used for traversing or searching tree or graph data structures. It explores the search space level by level starting from the root (or initial node):

- First, it visits all nodes at depth 0 (the root).

- Then, it visits all nodes at depth 1.
- Next, it visits all nodes at depth 2, and so on.

BFS guarantees that the first time a goal node is encountered, it is the shallowest (minimum depth) goal node, making BFS useful for finding the shortest path in an unweighted graph.

**BFS Algorithm**

BFS can be implemented using a FIFO (First-In-First-Out) queue to keep track of the frontier nodes:

1. Initialize a queue and insert the root node (or initial state).
2. Repeat until the queue is empty:
   - Remove the first node from the queue (front of the queue).
   - Check if this node is the goal node. If yes, return the solution path.
   - Otherwise, expand the node and add all its unexplored successors to the back of the queue.
3. If the queue becomes empty and no goal is found, the search fails.

**Pseudocode:**

text

```
BFS(problem):
  initialize the frontier using FIFO queue with the initial state
  while frontier is not empty:
    node = frontier.dequeue()
    if node.state == goal:
      return solution(node)
    for each child in expand(node):
      if child not in frontier and not in explored:
        frontier.enqueue(child)
  return failure
```

**Time Complexity of BFS**

- Assume the branching factor (maximum number of successors of any node) is **b**.
- Let the shallowest goal node be at depth **d**.

At each level **i** (0 to d), BFS explores all nodes at that depth before moving deeper.

- Number of nodes at depth $i = b^i$.
- Total nodes generated up to depth $d = b^0 + b^1 + b^2 + \cdots + b^d \approx O(b^d)$. d

The worst-case time complexity is thus:

$$O(b^d)$$

**Space Complexity of BFS**

BFS stores all nodes in the frontier and explored sets at a given depth.

- At depth d, the number of nodes in the frontier can be as large as $b^d$.
- Hence, space complexity is also:

$$O(b^d)$$

This high memory requirement can be a limitation for BFS in large or infinite state spaces.

## 6. Differentiate between Hill-Climbing and Simulated Annealing in local search techniques.

| Aspect | Hill-Climbing | Simulated Annealing |
|---|---|---|
| **Basic Principle** | Moves only to better neighbors (improves state) | Allows moves to worse states with some probability |

| | | |
|---|---|---|
| **Handling Local Maxima** | Can get stuck in local maxima | Can escape local maxima due to occasional "bad" moves |
| **Exploration vs Exploitation** | Exploits by always choosing the best neighbor | Balances exploration and exploitation via probability |
| **Move Selection** | Greedy, always selects best neighboring state | Probabilistic, accepts worse states sometimes |
| **Convergence** | Often converges prematurely at local max or plateau | Can converge to global optimum over time |
| **Dependence on Initial State** | Highly dependent, poor starting point leads to poor result | Less dependent due to probabilistic moves |
| **Memory Requirements** | Uses very little memory, only current state and neighbors | Similar low memory requirement |
| **Completeness** | Incomplete, may fail to find global optimum | More complete, can find global optimum given time |
| **Algorithm Complexity** | Simpler to implement and understand | More complex due to cooling schedule and probabilities |
| **Application Domains** | Suitable for problems with smooth landscapes | Better for rugged landscapes with many local optima |

## 7. Elaborate Depth-First Search (DFS) with its advantages and disadvantages.

**What is Depth-First Search (DFS)?**

Depth-First Search (DFS) is a graph or tree traversal algorithm that starts at the root (or an arbitrary node in a graph) and explores as far down a branch as possible before backtracking. It follows a path from the starting node to its deepest descendant, then backtracks to explore other sibling nodes, continuing this process until all nodes have been visited or a goal is found.

DFS can be implemented using recursion or with an explicit stack structure to keep track of the path from the root to the current node, aiding in backtracking when a dead end is reached.

**Working Principle of DFS:**

- Begin at the root node.
- Explore a path by visiting an adjacent unvisited node.
- Continue down that path until no further unvisited nodes are reachable (a dead end).
- Backtrack to the last node with unexplored neighbors and repeat.
- Continue until every node reachable from the starting point is visited.

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**Advantages of Depth-First Search:**

- **Memory Efficient:** DFS only needs to store nodes along the current path from the root to the deepest node, typically using a stack of depth O(d)O(d)O(d), where ddd is the maximum depth. This makes it much less memory intensive compared to breadth-first search, which must store all nodes at a given level.
- **Implementation Simplicity:** DFS is straightforward to implement recursively, leading to concise and elegant code.
- **Good for Deep Solutions:** If a solution exists deep in the tree (or graph), DFS might find it without exploring many nodes at shallower depths.
- **Useful in Applications:** DFS is fundamental in various algorithms such as cycle detection, pathfinding from one node to another, topological sorting, and finding strongly connected components.

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**Disadvantages of Depth-First Search:**

- **Possibility of Getting Stuck:** DFS can get trapped going down an infinitely deep (or very long) path if the graph is infinite or contains cycles without proper checks. This can cause non-termination.

- **Not Guaranteed to Find the Shortest Path:** DFS may find a solution quickly but not always the shortest or optimal path because it explores paths deeply without considering their cost or length.
- **Incomplete in Infinite Spaces:** Without depth limits, DFS might fail to find a solution in infinite or very large search spaces. Imposing a depth limit can help, but then the chosen cutoff may miss solutions or incur extra time if too large.
- **No Optimality Guarantee:** If multiple solutions exist, DFS offers no assurance that the first solution found is the best one in terms of cost or path length.

## UNIT 3

## 8. Explain the Min-Max algorithm with a suitable game tree diagram.

### What is Min-Max Algorithm?

The **Min-Max algorithm** is a decision-making and game theory algorithm primarily used for two-player turn-based games—such as chess, tic-tac-toe, or checkers—where the players have opposing goals. The algorithm assumes both players play optimally:

- The **Maximizing player (MAX)** aims to maximize their score (or utility).
- The **Minimizing player (MIN)** aims to minimize MAX's score.

The algorithm explores all possible moves (game states) to a certain depth and assigns utility values to terminal states (game results). It then backs up these values recursively through the game tree to decide the best move for MAX, assuming MIN will try to minimize MAX's payoff.

### How Min-Max Algorithm Works

1. **Game Tree Generation**:
   From the current state (root), the algorithm generates all possible moves, creating a tree of game states. Each node represents a game state.
2. **Terminal States Evaluation**:
   Terminal nodes (end of game, or depth limit reached) are evaluated with a utility function providing values indicating how favorable the outcome is for MAX (e.g., +1 for a win, -1 for a loss, 0 for a draw).
3. **Recursive Back-Up of Values**:
   - At MAX nodes (MAX's turn), the node's value is the maximum of the values of its children because MAX wants to maximize utility.
   - At MIN nodes (MIN's turn), the node's value is the minimum among the children, reflecting MIN's goal to minimize MAX's utility.
4. **Optimal Move Selection**:
   At the root, MAX chooses the child move with the highest backed-up value, assuming both players play optimally from there on.

### Pseudocode Overview

python

```
def minimax(node, depth, isMaximizingPlayer):
  if node is terminal or depth == 0:
    return utility(node)

  if isMaximizingPlayer:
    maxEval = -infinity
    for child in children(node):
      eval = minimax(child, depth - 1, False)
      maxEval = max(maxEval, eval)
    return maxEval
  else:
    minEval = infinity
    for child in children(node):
      eval = minimax(child, depth - 1, True)
      minEval = min(minEval, eval)
    return minEval
```

**Simple Min-Max Game Tree Diagram Example**

Consider a small game tree where MAX starts the game and chooses between two moves, and MIN responds with two possible responses for each:

```
           [A] MAX
            /     \
     [B] MIN     [C] MIN
       /   \     /   \
     +1    -1   0    +1
```

- Leaf nodes have utility values: +1, -1, 0, +1 from MAX's perspective.
- At MIN nodes B and C:
  - MIN chooses the minimum value among children.
  - At B: min(+1, -1) = -1
  - At C: min(0, +1) = 0
- At MAX node A:
  - MAX chooses the maximum value among children.
  - max(-1, 0) = 0

Thus, the optimal value for MAX at A is 0, so MAX will choose the path through node C.

**Explanation**

- MAX's goal is to pick moves leading to the highest utility considering MIN's best counter moves.
- MIN aims to minimize MAX's utility.
- The algorithm recursively travels down the tree evaluating moves and backs up the best values.
- This ensures decision-making accounts for the opponent's best strategies.

## 9. Explain Alpha-Beta pruning.

**Alpha-Beta Pruning Explained**

**Alpha-Beta pruning** is an advanced search technique used in game-playing AI – most notably in two-player games like chess or tic-tac-toe – to make optimal decisions more efficiently. It operates as an enhancement to the basic **Minimax algorithm**, allowing the AI to ignore branches of the game tree that cannot possibly affect the final outcome.

**What Problem Does It Solve?**

The standard minimax algorithm explores all possible moves and counter-moves until reaching terminal states, which can be computationally expensive as the number of possibilities increases exponentially. Alpha-Beta pruning helps by eliminating large portions of the search tree that do not require exploration, thereby reducing computation time without sacrificing optimality.

**How Does Alpha-Beta Pruning Work?**

- Two parameters are maintained during traversal:
  - **Alpha (α):** The best (highest) value the maximizer (MAX) player can guarantee so far along its path.
  - **Beta (β):** The best (lowest) value the minimizer (MIN) player can guarantee along its path.
- When traversing nodes:
  - If the value at a node proves to be worse than what the MAX or MIN can achieve with current alpha or beta, further exploration of that node is abandoned (pruned).
- The condition for pruning is **$\alpha \geq \beta$** at any point; the node or its successors need not be explored further.

**Steps in Alpha-Beta Pruning:**

1. Start with initial values: $\alpha = -\infty$ and $\beta = +\infty$.
2. Traverse the game tree using recursive depth-first search (like minimax), updating α and β at each node.
3. Prune (discard) a node when it becomes clear that its value cannot improve the outcome for MAX or MIN regarding current α/β bounds.

4. Alpha is updated only during MAX’s turn and Beta only during MIN’s turn.

**Efficiency:**

- Without pruning, minimax explores O(bd)O(b^d)O(bd) nodes, where bbb is the branching factor and ddd is depth.
- With alpha-beta pruning (in ideal circumstances), only O(bd/2)O(b^{d/2})O(bd/2) nodes are searched – nearly doubling the search depth achievable in the same time.

**Key Points:**

- **Alpha**: Best score achievable for MAX so far (initialized at –∞).
- **Beta**: Best score achievable for MIN so far (initialized at +∞).
- **Pruning Condition**: Stop searching a branch when α ≥ β.
- **Optimality**: The final decision will be the same as if the full tree was searched; only unnecessary parts are skipped.

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## 10. Discuss Constraint Propagation in CSP with an example.

**Constraint Propagation in Constraint Satisfaction Problems (CSP)**

**Constraint propagation** is a technique used in solving CSPs to systematically reduce the search space by deducing new constraints from the existing ones, thereby simplifying the problem before or during the search process. The goal is to enforce local consistency and eliminate values from variable domains that cannot participate in any valid solution, based on the constraints already imposed.

**How Constraint Propagation Works**

- When a variable is assigned a value, the implications of this assignment are propagated to other variables, often removing incompatible values from their domains.
- This is done repeatedly, propagating constraints until no further reductions in domains are possible or a contradiction is found (i.e., a variable ends up with an empty domain, signaling a need to backtrack).

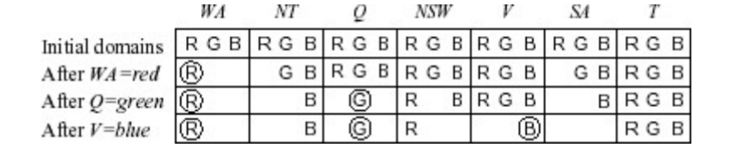
**Methods of Constraint Propagation**

Some common forms:

- **Forward checking:** When a variable is assigned, remove illegal values from neighbors' domains.
- **Arc consistency:** For every constraint between two variables (say, X and Y), ensure that for every value in X's domain, there is a compatible value in Y's domain.

**Example: Map Coloring with Constraint Propagation**

Consider the **Australia map coloring problem** where each region must be colored so that no neighboring regions have the same color. The available colors are red, green, and blue, and the regions are WA, NT, Q, NSW, V, SA, and T.Unit-III-Notes.pdf



| | *WA* | *NT* | *Q* | *NSW* | *V* | *SA* | *T* |
|---|---|---|---|---|---|---|---|
| Initial domains | R G B | R G B | R G B | R G B | R G B | R G B | R G B |
| After *WA=red* | Ⓡ | G B | R G B | R G B | R G B | G B | R G B |
| After *Q=green* | Ⓡ | B | Ⓖ | R B | R G B | B | R G B |
| After *V=blue* | Ⓡ | B | Ⓖ | R | Ⓑ | | R G B |

**Figure 3.18 The progress of a map-coloring search with forward checking. WA = *red* is assigned first; then forward checking deletes *red* from the domains of the neighboring variables *NT* and *SA*. After *Q* = *green*, *green* is deleted from the domain of *NT, SA*, and *NSW*. After *V* = *blue, blue,* is deleted from the domains of *NSW* and *SA*, leaving *SA* with no legal values.**

**Step-by-Step Illustration**

1. **Initial Assignment:**
   - Assign WA = red.
   - Forward checking removes 'red' from domains of WA's neighbors: NT and SA.
2. **Next Assignment:**
   - Assign Q = green.
   - Forward checking removes 'green' from NT, SA, and NSW (since Q is neighbor to NT, SA, and NSW).
3. **Further Assignment:**
   - Assign V = blue.
   - Forward checking removes 'blue' from NSW and SA.
4. **Detection of Failure:**
   - At this stage, it may happen that SA has no legal colors left in its domain, resulting in a **dead end** and forcing the algorithm to backtrack and try different assignments.

**Visualization**

- Every variable's domain is updated dynamically as assignments are made and constraints are propagated.

- The process helps in early detection of failures, preventing wasted effort on impossible paths.

**11.Question:**

**Explain the Backtracking Search method in Constraint Satisfaction Problems (CSP) with reference to the Map Coloring Problem below. Show each variable assignment step in order. Indicate any conflicts, backtracks, and the use of forward checking or simple consistency checks (if applied). Provide one consistent coloring solution or state if none exists for the given colors.**

**Regions and adjacencies:**

- **A is adjacent to B and C**
- **B is adjacent to A, C, and D**
- **C is adjacent to A, B, and D**
- **D is adjacent to B and C**

**Available colors: {Red, Green, Blue}**

**Answer:**

**Backtracking Search for Map Coloring CSP**

**Step 1: Assign color to A**

Choose **A = Red**.

*Forward checking:*

Remove Red from the domains of B and C (since they are adjacent to A).

- B's domain: {Green, Blue}
- C's domain: {Green, Blue}

**Step 2: Assign color to B**

From B's domain {Green, Blue}, select **B = Green**.

*Forward checking:*

Remove Green from the domains of C and D (adjacent to B).

- C's domain: {Blue}
- D's domain: {Red, Blue}

**Step 3: Assign color to C**

From C's domain {Blue}, assign **C = Blue**.

*Forward checking:*

Remove Blue from D's domain (adjacent to C).

- D's domain: {Red}

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**Step 4: Assign color to D**

From D's domain {Red}, assign **D = Red**.

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**Summary of Assignments:**

- A = Red
- B = Green
- C = Blue
- D = Red

**Conflict and Backtracking:**

- No conflicts arose during any assignment steps.
- Forward checking helped by pruning inconsistent color choices, improving efficiency.
- Since all adjacency constraints are satisfied (no two adjacent regions have the same color), backtracking was not needed.

**Final consistent coloring solution:**

A = Red, B = Green, C = Blue, D = Red