

# A\* ALGORITHM

Search algo used to find shortest path from a start node to a goal node in a weighted graph

- Combines features of DIJKSTRA'S Greedy Best-First search
- Applications
  - Robotics
  - Navigation system
  - Game development
  - Geographic Information System (GIS)

Components	Heuristic Function	Cost Function
Start Node	Estimates the cost from the current node to the goal	Actual cost from start node to the current node - weight
Goal Node		
Open List		
Closed List		

Evaluation Function:  $f(n) = g(n) + h(n)$

- Initialization: Add the start node to the open list with  $f(\text{start}) = h(\text{start})$

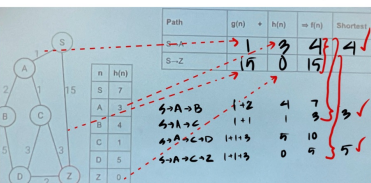
Main Loop: While the open list is not empty  
SELECT NODE: Choose the node with the lowest  $f$  value from the open list  
GOAL CHECK: If it's the goal node, reconstruct the path  
GENERATE SUCCESSORS: Evaluate each neighbor node  
UPDATE LISTS: Move the current node to the closed list and update the open list with new nodes

PATH RECONSTRUCTION: Trace back from the goal node to the start node to build the path

Time Complexity:  $O(b^d)$   
 $b$ : branching factor  
 $d$ : depth of the shortest path

Space Complexity:  $O(b^d)$   
needs to store nodes in the open/closed lists

Better heuristics lead to more efficient search and reduced time complexity



n	h(n)
A	7
B	10
C	15
D	1
E	8
F	1
G	0
S	10

Path	g(n)	h(n)	f(n)	Shortest
S	0	10	10	
S→A	3	7	10	
S→B	2	10	12	X
S→C	1	15	16	X
S→D	3+6	1	10	
S→E	3+4+1	1	11	
S→F	3+6+1+1	0	11	

# R\* ALGORITHM

R\* = Rapidly-Exploring Random Tree Star

R* (Rapidly-Exploring Random Tree Star)	Algorithm Steps
<ul style="list-style-type: none"><li>Purpose: Efficiently explore and find optimal paths in high-dimensional spaces.</li><li>Use Case: Motion planning in robotics and autonomous systems.</li></ul> <p>Key Features:</p> <ul style="list-style-type: none"><li>Rapid Exploration: Builds a tree by rapidly exploring the space.</li><li>Optimization: Continuously refines the path to find an optimal solution.</li></ul>	<ol style="list-style-type: none"><li>Initialization: Start with an initial tree from the start point.</li><li>Random Sampling: Generate random points in the space.</li><li>Tree Expansion: Expand the tree towards the randomly sampled points.</li><li>Path Optimization: Refine paths to improve the quality and efficiency.</li></ol>

- R\* Heuristic
  - R\* may incorporate heuristic biases to guide the sampling process towards promising regions of the space.
  - Goal biasing: increasing the probability of sampling near the goal to improve convergence towards the target.
- Distance Awareness: Adjusting sampling strategies to avoid areas with high obstacle density.
- Informed Sampling: R\* can use informed sampling techniques to focus exploration efforts on regions with higher likelihood of leading to an optimal path.
- Density-Based Sampling: Sampling more frequently in regions with lower density of obstacles.

# GAME PLAY

Stiffing Algorithms	Decision-Making Algorithms
<p>Purpose: To find the most efficient path from a starting point to a target in a game environment (e.g., a grid, graph, or map).</p> <p>Focus: Calculating the movement of a single path, typically for characters or objects in a game or robotics in real-world navigation.</p> <p>Applications: Navigation systems, game AI for NPC movement, robotic motion planning, and route optimization in logistics.</p>	<p>Purpose: To make optimal decisions based on evaluating possible outcomes or moves, often in a competitive or uncertain environment.</p> <p>Focus: Choosing the best action or strategy based on the current state and potential future states.</p> <p>Applications: Strategic games (chess, Go), real-time strategy games, AI agents in simulations, and autonomous decision systems in robotics.</p>

- A\*: Combines Dijkstra's algorithm with heuristics for efficient pathfinding.

Dijkstra's: Finds the shortest path in graph w/o heuristics  
BFS: Explores the shortest path in unweighted graph

Pathfinding	Decision-Making
<ul style="list-style-type: none"><li>Structure: Typically represented as a graph, with nodes as positions and edges as possible moves.</li><li>Heuristics: Used to estimate the cost to reach the goal (e.g., a grid-based distance heuristic).</li><li>Input: Graph or map with nodes and edges, start and target positions.</li><li>Output: The shortest or most optimal path from start to target.</li></ul>	<p>Decision-Making:</p> <ul style="list-style-type: none"><li>Structure: Often represented as a decision tree, with nodes as game states and edges as possible moves or actions.</li><li>Heuristics: Can be deterministic or probabilistic; they involve estimating the value of different actions or states.</li><li>Input: Current game state or situation, possible actions, and rules of the environment.</li><li>Output: The best action or sequence of actions based on the evaluation of possible outcomes.</li></ul>

# HEURISTIC SEARCH

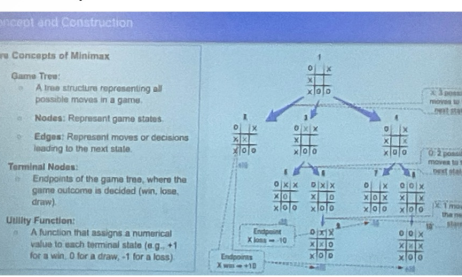
Heuristic Search Algorithms

- Purpose: Used to find optimal paths or solutions in various problems such as pathfinding and puzzle solving.
- Example: A\* Algo is a popular heuristic search algo for finding the shortest path in graphs.
- Key Concepts
  - Admissibility: Ensures the heuristic never overestimates the cost to reach the goal.
  - Consistency: Ensures the heuristic satisfies the triangle inequality.

- Consistent Heuristic: Heuristic Function  $h(n)$  is consistent or monotonic if for every node  $n$  and every successor  $n'$  of  $n$  reached by an edge  $e$ ,  $h(n) \leq c(e) + h(n')$ .
- Admissible Heuristic:  $h(n)$  is admissible if it never overestimates the cost to reach the goal.
- Guarantees optimality
  - Example: In pathfinding problems, straight line distance from a node to the goal is often admissible.
- Consistent heuristics ensure A\* will expand nodes in proper order, guaranteeing completeness & optimality.

# MINIMAX

DECISION MAKING:  
Minimax Algorithm: Used in two-player zero-sum games where one player's gain is equivalent to the other player's loss.  
↳ Recursive decision-making algo used for minimizing the possible loss in a worst-case scenario



- KEY FEATURES:
  - COMPLETE: If a game tree is finite, Minimax will eventually find the optimal path.
  - DETERMINISTIC: Always produces the same result given the same game state.
  - OPTIMAL: Find the best move assuming both play optimally.

Time Complexity:  $O(b^d)$ ,  $b$ : branching factor,  $d$ : tree depth  
Space Complexity:  $O(bd)$ , depending on depth/breadth of game tree

# Alpha-Beta Pruning

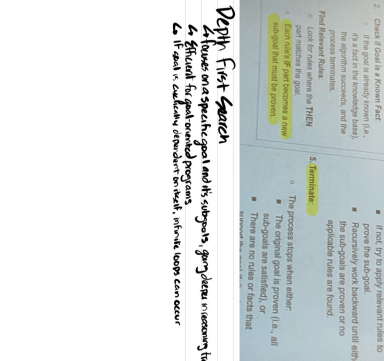
Branching Factor: The number of branches (children) a node has corresponds to the possible actions available to the player at that point in the game. For example:	No Theoretical Limit: There's no strict limit on Minimax regarding the number of branches per node. The algorithm will explore all possible moves from each game state.
<ul style="list-style-type: none"><li>Tic-Tac-Toe: A node might have up to 9 branches initially (one for each empty square), decreasing as the game progresses.</li><li>Chess: A node might have dozens of branches, depending on the possible legal moves.</li><li>Go: A lot more possible branches (positions for the next stone).</li></ul>	<p>Implications of High Branching Factor:</p> <ul style="list-style-type: none"><li>Increased Complexity: A higher branching factor leads to a larger game tree, increasing the computational cost of evaluating all possible outcomes.</li><li>Efficiency Considerations: Techniques like Alpha-Beta pruning become more critical in managing large branching factors to keep the algorithm feasible.</li></ul>

The sequence in which leaf nodes are evaluated during the Minimax algorithm significantly impact

Alpha Cutoff (Maximizer)  
Alpha is the best score the maximizer can guarantee at that point in the tree

Beta Cutoff (Minimizer)  
Beta is the best score the minimizer can guarantee at that point in the tree

Initial Alpha & Beta → Alpha = -∞ or Beta = ∞  
Maximizer's Turn (max node)  
↳ For each child of the current node, evaluate the child node, update alpha, check for beta cutoff  
Minimizer's Turn (min node)  
↳ For each child of the current node, evaluate the child node, update beta, check for alpha cutoff



# MONTE CARLO APPROACH

- Monte Carlo Tree Search (MCTS)
  - Heuristic search algo that uses randomness to explore the game tree.
  - It builds the tree incrementally, focusing on promising nodes.
- BASIC STEPS
  - Selection: Start at the root node (current game state) & recursively select child nodes using a strategy like Upper Confidence Bound until you reach a leaf node.
  - Expansion: If leaf node is not a terminal state, expand the tree by adding one or more child nodes, corresponding to possible moves.
  - Simulation: Perform a random playout from the newly expanded node until the game reaches a terminal state. The result of this random playout (win/loss) provides an estimate of the value of the node.
- Backpropagation

Define the problem  
Start by clearly identifying the problem or quantity you want to estimate. This could be numerical results, such as the value of an integral, the outcome of a probabilistic process, or the approximation of a constant.  
Set up a random model  
Translate the problem into form where random variables or random samples

Path Finding (Graph)

Path Finding (Graph)	Game Play (Tree)
<ul style="list-style-type: none"><li>BFS: Exhaustive search</li><li>DFS: Greedy search</li><li>Dijkstra's: Deterministic optimal</li><li>A*: Heuristic driven</li><li>D*: Dynamic change</li><li>R*: Random exploring of hyperspace</li></ul>	<ul style="list-style-type: none"><li>Minimax<ul style="list-style-type: none"><li>DFS-like</li><li>Backpropagation</li></ul></li><li>Alpha-Beta Pruning: Deterministic reduction of game tree</li><li>IDA*: Combine DFS + BFS</li><li>MCTS: Dynamic heuristic ⇒ dynamic threshold</li><li>Random exploring</li><li>Softmax Search</li><li>Probabilistic exploring + exploiting</li></ul>

Forward/Backward Chaining



Forward Chaining: Ideal for systems where we want to explore all possible outcomes from a set of facts.

Backward Chaining: Better for proving specific goals or hypotheses.

Comparison of Forward and Backward Chaining

Feature	Forward Chaining	Backward Chaining
Purpose	Data-driven (from facts to conclusions)	Goal-driven (from goal to facts)
Deriving conclusions	Deriving all possible facts/conclusions	Proving specific goals or hypotheses
Efficiency	Can be inefficient if too many irrelevant rules fire	More efficient for solving specific goals
Search Strategy	Breadth-first (explores all rules)	Depth-first (focuses on a goal)
Typical Use Case	Monitoring systems, expert systems (medical diagnosis)	Problem-solving, decision-making, theorem proving
Complexity	Can be expensive if many rules fire	Can result in deep recursion for complex goals

Forward Chaining: Data-Driven (Starts with known facts & rules)

- Initialize Knowledge Base
- Start with set of facts
- Define a set of if-then rules

Match Rules  
For each rule, check if conditions are satisfied by current facts in base. This is called Rule Matching.

Apply Rules  
Update Knowledge Base

Repeat  
Terminate

Backward Chaining

Backward Chaining: Goal-driven (Starts with a goal & works backwards to find facts)

- Initialize Knowledge Base
- Start with set of facts
- Define a set of if-then rules

Match Rules  
For each rule, check if conditions are satisfied by current facts in base. This is called Rule Matching.

Apply Rules  
Update Knowledge Base

Repeat  
Terminate

Problem Solving Algorithms, Expert Systems Solutions, Knowledge Representation Reasoning	Rete Algorithm
Problem Solving Algorithms	Ensuring efficient pattern matching even when dealing with a large set of rules and facts
Knowledge/Heuristics -> numbers	Decouple rule evaluation from execution sequencing
use numbers to drive the problem solving strategy	Alpha-Beta Network/Node
Expert Systems Solutions	Alpha Node - These handle simple tests on individual facts
Knowledge -> Logic-> Data Structure	Comparing a fact's attribute to a constant value
Run data through logic -> Flow facts through data structure, to make decisions	Beta Node - These combine multiple facts
Knowledge Representation Reasoning	When a rule has conditions that depend on more than one fact
Knowledge/Relationships -> Taxonomy & Ontology	Rete avoids re-evaluating all rules and facts each time new data is introduced
Web Data -> Semantically Linked Data	Using a data structure (called the Rete Network)
Querying -> Reasoning	Convert Rules -> Objects
Learning-Based AI vs Classic AI	Advantages
Learning-Based AI (knowledge driven rules)	Speed as it takes the advantage of structural similarity
Rules and data are put into classical programming, which outputs answers	Disadvantages
Rules => Knowledge -> Intelligence	Conflict Resolution
Classic AI (data driven data)	<b>Definition:</b> When multiple rules are applicable at the same time, conflict resolution strategies determine which rule to apply
Data and answers put into machine learning and output "rules" - Training phase	With forward chaining, the Rete network would create partial matches for each of these rules based on incoming patient data. As new symptoms are added, the network efficiently updates natchez. When multiple rules are ready to fire, a conflict resolution strategy determines which diagnosis to make first, based on priority or specificity
Data is put into Inferencing ("rules") and outputs Answers	This combination of the rete algorithm and conflict resolution strategies allows systems to efficiently handle large numbers of rules and facts
ML Problems and Applications	Strategies
House Price Prediction	Recency, specificity, priority, random
Data - Features like square footage, number of bedrooms, neighborhood, etc.	Recency- Rule that matches the most recent data is given priority
Label - Price of the house	Specificity - More specific rules are given priority
Model - Linear Regression	Priority Rules - predefined priorities assigned by the system designer
Answer - Prediction of the house price (Regression)	Random - If no clear priority exists
Customer Churn Prediction	Algos
Data - Features like customer age, contract length, monthly charges, customer service interactions, etc.	Pqueue, salience, heuristic evaluation
Label - Whether the customer will leave the service	Expert Systems Examples
Model - Logistic Regression or Decision Trees	Production Rules (Rule-Based Systems)
Answer - Prediction of whether customer will churn (Classification)	Semantics
Data vs Label for Learning	Frames
Dog vs Cat	Taxonomy is a group of related thing
Data: Image features extracted from pixels or convolution layers (images of dogs & cats)	Define categories within a single domain
Label: The class (1 for cat, 0 for dog)	Ontology captures multidimensional relationships
Handwritten Digit Recognition (MNIST dataset)	Connects taxonomies to provide rich information about the business environment
Data: Images of handwritten digits (28x28 pixel images)	Interrrelationships among the entities in the taxonomy are the essence of ontology
Label: The actual digit (0-9) corresponding to the image	Therefore, the ontology reflects a broad view of the business and a detailed description of its components
Model: Convolutional Neural Network (CNN) or k-Nearest Neighbors (k-NN)	Semantic web stack
Answer: Classification on digit (Classification)	Ontology management tools
Images of various objects	Ontology based data access
Data: Small images of various objects like airplanes, cars, bird, cat, deer, dog, etc.	Specialized ontologies and models
Label: The actual name of the object corresponding to the image	Linked data platforms
Model: CNN	Owl reasoners
Answer: Classification of object	Querying , ontologies, rules, taxonomies, Data interchange
Object Recognition (labeling is very important)	Syntax
Face Detection vs Face Recognition	Identifiers, character Set
Automatic License Plate Recognition	RDF - Resource Description Framework - Standard for representing data on the web
Content Derivation	Flexible and powerful framework for representing structured data
Colorization	Enable linking of diverse datasets, making it essential for the semantic web
Supervised Learning	General taxonomy framework for representing interconnected data on the web
Type of machine learning where a model is trained on labeled data	RDF statements are used for describing and exchanging metadata
Model is from human knowledge	Which enables standardized exchange of data based on relationships
Parameters are from training (examples)	Developed by W3C as a key component of the Semantic Web
Key Algos	Purpose
Linear Regression - Regression problems	Information in a structured way so machines can understand and process relationships between entities
predicting house price based on its size and location	Enables the creation of linked data,
Logistic Regression - Binary classification problems	RDF Data Model is built around triples
Predicting whether a customer will buy a product (y/n , 1/0)	Example: (John, hasName, "John Smith")
Decision Trees - Classification and Regression	Subject, Predicate, Object
Predicting which loan applicants are likely to default	RDF uses XML syntax for structuring triples
Support Vector Machines (SVM) - Classification	RDFS (S+Schema)
Classifying emails as spam or not spam	Extends RDF by providing semantics for concepts like classes and properties
Linear Regression	OWL (Web Ontology Language)
Regression - return to a former or less developed state	Based on rdf but more expressive
A measure of the relation between the mean value of one variable (e.g. output) and corresponding values of other variables (e.g. time and cost)	Formal language designed for representing complex knowledge about things relationships and categories on the web
In context of stats and ml	Purpose
Regression refers to a type of predictive modeling technique that estimates the relationships between a dependent variable (outcome/target) and one or more independent variables (predictors or features)	Enables machines to understand and reason over structured data
The primary goal of regression is to predict the value of the dependent variable based on the input feature	Standardized by the W3C for the Semantic Web
Regression tries to "fit" a model to observed data in such a way that we can make predictions about future data points	RDF doesn't have the power to reason, just to capture and structure
Goal of linear regression is to find the model parameters that best fit the data	Key Concepts and Levels
Logistic Regression	Classes, individuals, properties, and axioms
Classification algorithm used to predict binary outcomes based on 1 or > independent variables	Class - Categories or types of things
Formula : $P(y=1 x)=1/(1+e^{-(B_0+B_1x_1+...+B_nx_n)})$	Subclassing
Output: probability value between 0 and 1, which is converted into a class label	(person, organization) (person-employee)
Example: Predicting whether a student will pass/fail based on study hours	>(John)
Sigmoid Function = Logistic Function	Individual - Specific instance of classes
Primary reason for using the sigmoid function is that it maps any real-valued number into a range between 0 and 1	Properties - Relationship between things
Crucial for logistic regression because we want to interpret output as prob	Object Properties
$\hat{o}(x)=1/(1+e^{-z})$ , where $z = (B_0+B_1X)$	Reasoning - process of inferring new knowledge from explicit facts and rules
As $z$ approaches $-\infty$ , sigmoid approaches 0	If John is an instance of manager, owl inferencing can conclude that John is also an employee and person
As $z$ approaches $+\infty$ , sigmoid approaches 1	Applications
This property makes it perfect for estimating the prob of binary outcome	Healthcare & biomedical ontologies, Gene ontology, Google's knowledge graph
Function has an S-shaped curve, providing a smooth transition between 0 and 1	RDF vs OWL
Allows model to represent probabilities in a way that reflects uncertainty	Rdf = smaller domain, mostly on taxonomies ( classifying )
Near midpoint, the output changes rapidly, making it sensitive to changes in input	Structure: Simple Triples (subject-predicate-objects)
Purpose: Used for predicting a binary outcome based on one or more independent vars	Better for lightweight flexible knowledge graphs where simplicity is key, and there's no deep reasoning or complex logic structures
Assumptions	Owl = Bigger domain. Bigger scope
Dependent Variable is binary (0,1)	Structure: triples with extended semantics (classes, properties, restrictions)
Independent Variables can be continuous or categorical	Suited for applications where you need to enforce strict ontological rules and enable reasoning engines to draw conclusions automatically from defined knowledge graph
Assumes a logistic relationship between independent and the log odds of the dependent variable	
Data Role:	
Similar to linear regression, but dependent variable is categorical	
Model estimates probability that given input point belongs to a particular category based on the independent variables	
Example: medical diagnosis scenario; independent variables = age, symptoms, test results to predict if patient has disease or not (1/0)	
Importance of Data	
Quality - quality of data directly impacts the accuracy of the model	
Feature Selection - choosing wrong independent variables can distort the predictions	
Volume - Sufficient volume helps in capturing the underlying patterns & relationships	
Decision Tree	
Construction	
Splitting - dataset split based on attribute that leads to highest information gain	
Recursive Partitioning - process continues recursively, splitting each subset furth	
Stopping Criteria - Algo stops when all data points are perfectly classified or other predefined stopping rules are met (max depth, minimum samples per leaf)	
Prediction - Once built, tree can predict output by navigating from root to leaf node for new input data	
Information Gain	
Entropy	
Gini Index - Measure of impurity or disorder used in decision trees	
Represents how often a randomly chosen element from the set would be incorrectly classified if it was randomly labeled according to the distribution of labels in the set	
Definition	
Gini(s) = 1 - sum of $i = 1$ to $n$ of	
Weighted Gini	
Gini(Split) = sum of $1$ to $k$ (( $ S_i / S $ ) x Gini( $s_i$ ))	
S = original set before split	
$S_i$ = one of the $k$ groups formed by the split	
$S_i$   = size (number of elements) in group $S_i$	

## 7. Knowledge Representation

- Ontologies:**
  - Structures that define relationships between concepts and connect taxonomies for reasoning over linked data.
- Taxonomy vs. Ontology:**
  - Taxonomy:** Categorizes items within a domain.
  - Ontology:** Defines relationships between taxonomies and connects domains for richer data representation.

## 8. Learning-Based AI vs. Classical AI

- Classic AI (Expert Systems):**
  - Rule-based systems that use predefined logic to infer conclusions from data.
- Learning-Based AI (Machine Learning):**
  - Data-driven models that learn patterns from data without pre-programmed rules. Includes neural networks, decision trees, and ensemble learning.

## 1. Artificial Intelligence (AI) - Classical Approaches

- Brief History of AI**
  - Alan Turing (1950):** Introduced the concept of the "universal machine" and the Turing Test.
  - John McCarthy (1956):** Coined the term "Artificial Intelligence" at the Dartmouth Conference.
  - Early Programs (1951):** Christopher Strachey wrote the first AI program, a checkers game.
- Ups and Downs of AI**
  - First AI Winter (1970s):** Reduced funding and interest due to unmet expectations.
  - Second AI Winter (Late 1980s - Early 1990s):** Expert systems struggled with scalability.
  - Resurgence in the 1980s:** Development of expert systems like MYCIN and XCON revived AI interest.

## 2. Search-Based Problem Solving

- Pathfinding Algorithms**
  - Breadth-First Search (BFS):** Explores nodes at the current depth before moving deeper. Ideal for unweighted graphs.
  - Depth-First Search (DFS):** Explores as far as possible along a branch before backtracking.
  - Dijkstra's Algorithm:** Uses a priority queue to explore the cheapest path first. Efficient for finding the shortest path in weighted graphs.
  - A Algorithm:\*** Combines Dijkstra's algorithm with a heuristic. Finds shortest paths efficiently with heuristic guidance.
  - D Algorithm:\*** Finds paths in dynamic environments and updates efficiently when obstacles change.
  - R Algorithm:\*** Used in high-dimensional motion planning, explores random points in space and refines the optimal path.

## 3. Game Playing

- Minimax Algorithm:**
  - Used in two-player games like chess or tic-tac-toe to find the optimal move assuming the opponent plays optimally.
- Alpha-Beta Pruning:**
  - Optimizes Minimax by pruning branches that don't affect the final decision.
- Monte Carlo Tree Search (MCTS):**
  - Uses random simulations to explore possible game states, focusing on the most promising moves.
- Softmax Search:**
  - Balances exploration and exploitation by probabilistically selecting moves, allowing exploration of less-promising moves.

## 4. Knowledge Representation and Reasoning

- Forward Chaining:**
  - A data-driven approach that applies rules to known facts to derive new facts.
- Backward Chaining:**
  - A goal-driven approach that starts with a goal and works backward to find supporting facts.
- Rete Algorithm:**
  - Efficient pattern matching algorithm used in large-scale rule-based systems to match facts with rules.

## 5. Machine Learning (ML)

- Supervised Learning**
  - Decision Trees:** Splits data based on features that lead to the highest information gain.
  - Random Forests:** An ensemble of decision trees that reduces overfitting and improves accuracy.
  - Gradient Boosting:** Sequentially builds models to correct errors of previous models. XGBoost is a popular, efficient implementation.
- Neural Networks**
  - Perceptron:** A simple linear classifier.
  - Multilayer Perceptron (MLP):** A network with multiple hidden layers, trained using backpropagation and gradient descent.

## 6. Heuristic Search

- Admissibility:**
  - Ensures that a heuristic never overestimates the true cost to reach the goal.
- Consistency:**
  - Ensures the heuristic obeys the triangle inequality, preserving optimality.
- Backward Heuristic:**
  - Used in dynamic environments to propagate changes from the goal backward, efficiently updating paths.

## 9. Comparing Algorithms

- Pathfinding Algorithms:**
  - Strengths:** Effective in static environments, providing optimal paths.
  - Limitations:** Struggle in dynamic environments where conditions change.
- Decision-Making Algorithms:**
  - Strengths:** Handle dynamic and competitive environments well, suitable for complex games.
  - Limitations:** Computationally expensive and may require approximations in large search spaces.