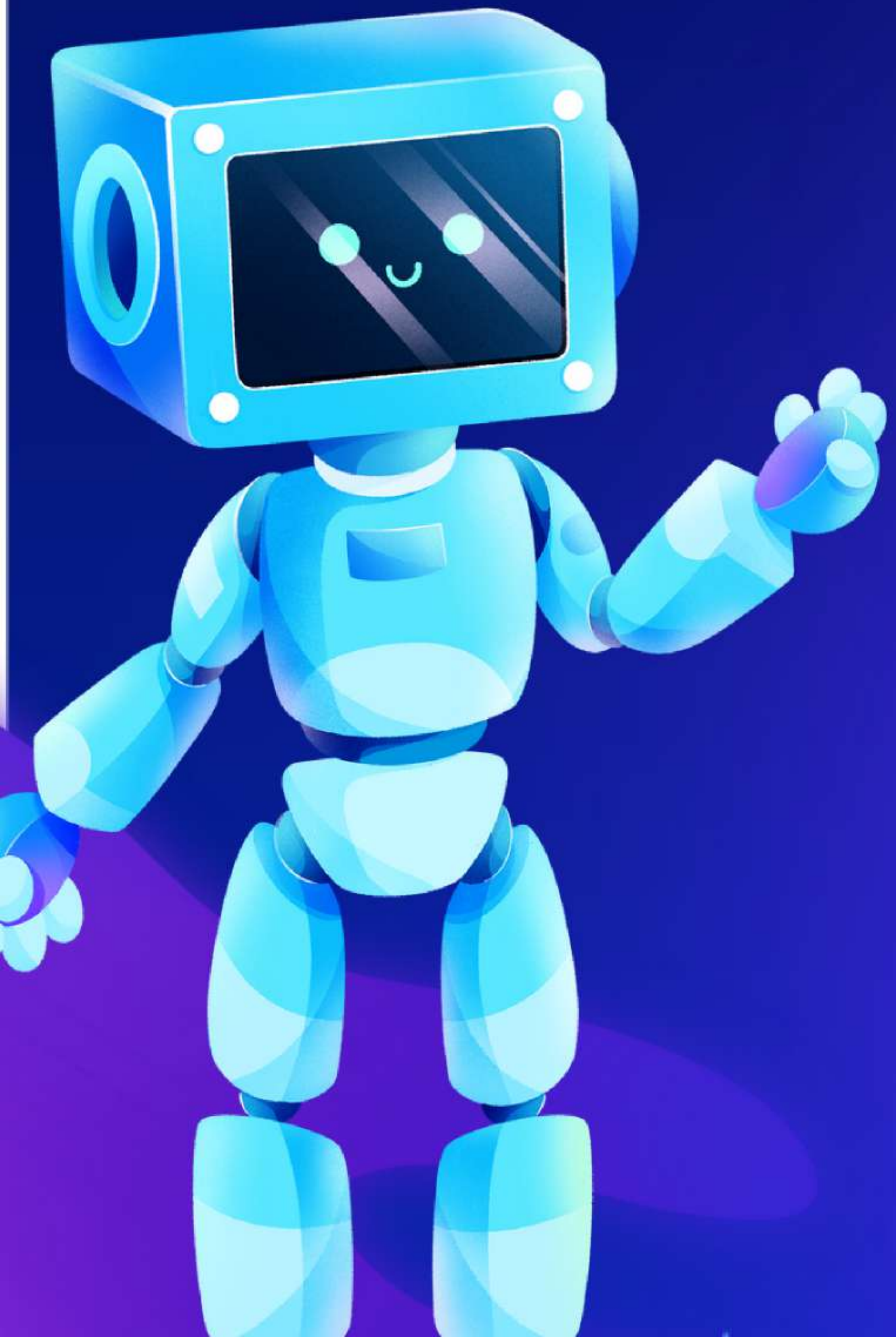
PLANNING IN THE REAL WORLD NON DETERMINISTIC DOMAINS



ARTIFICIAL INTELLIGENCE

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2022510044

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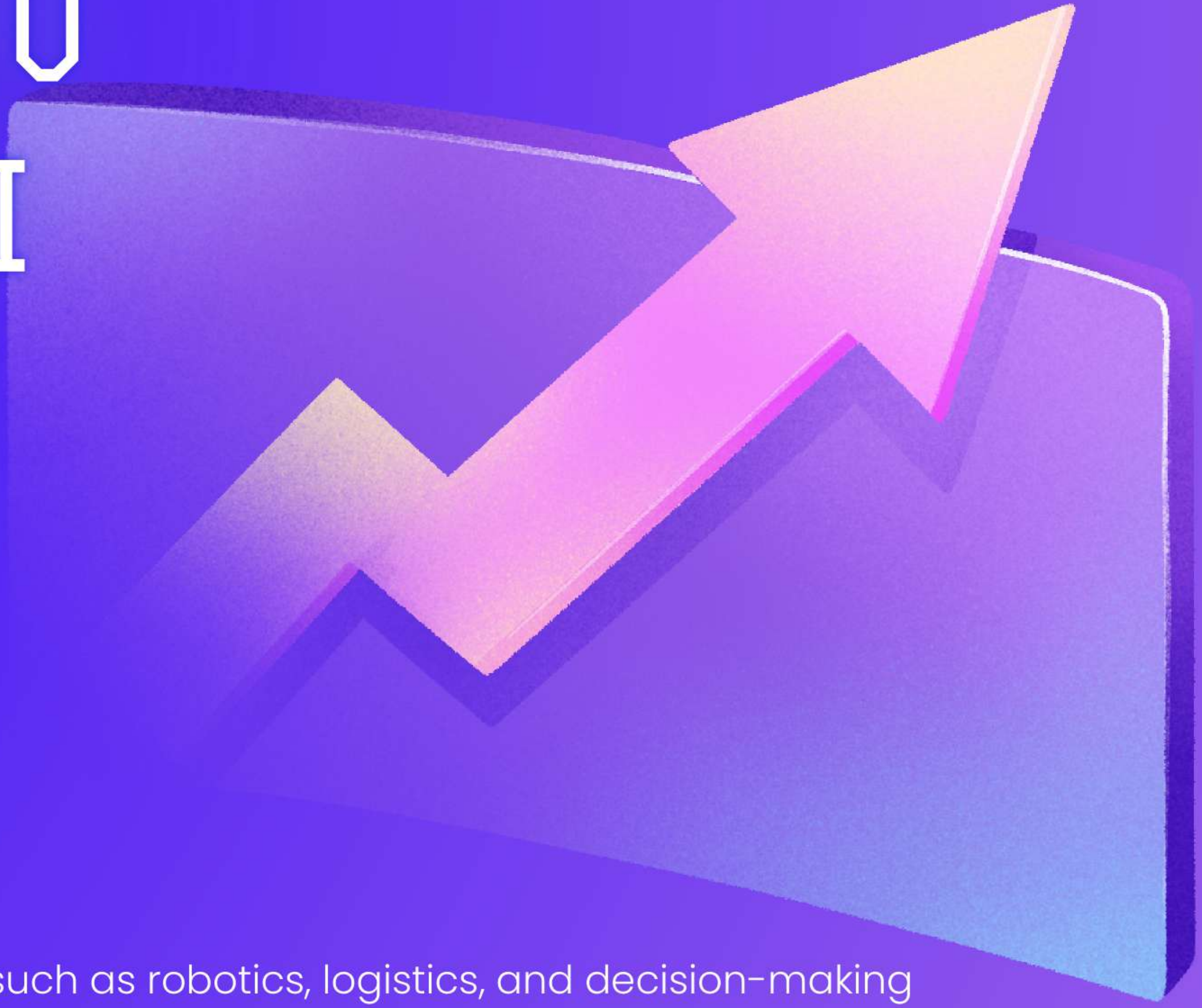


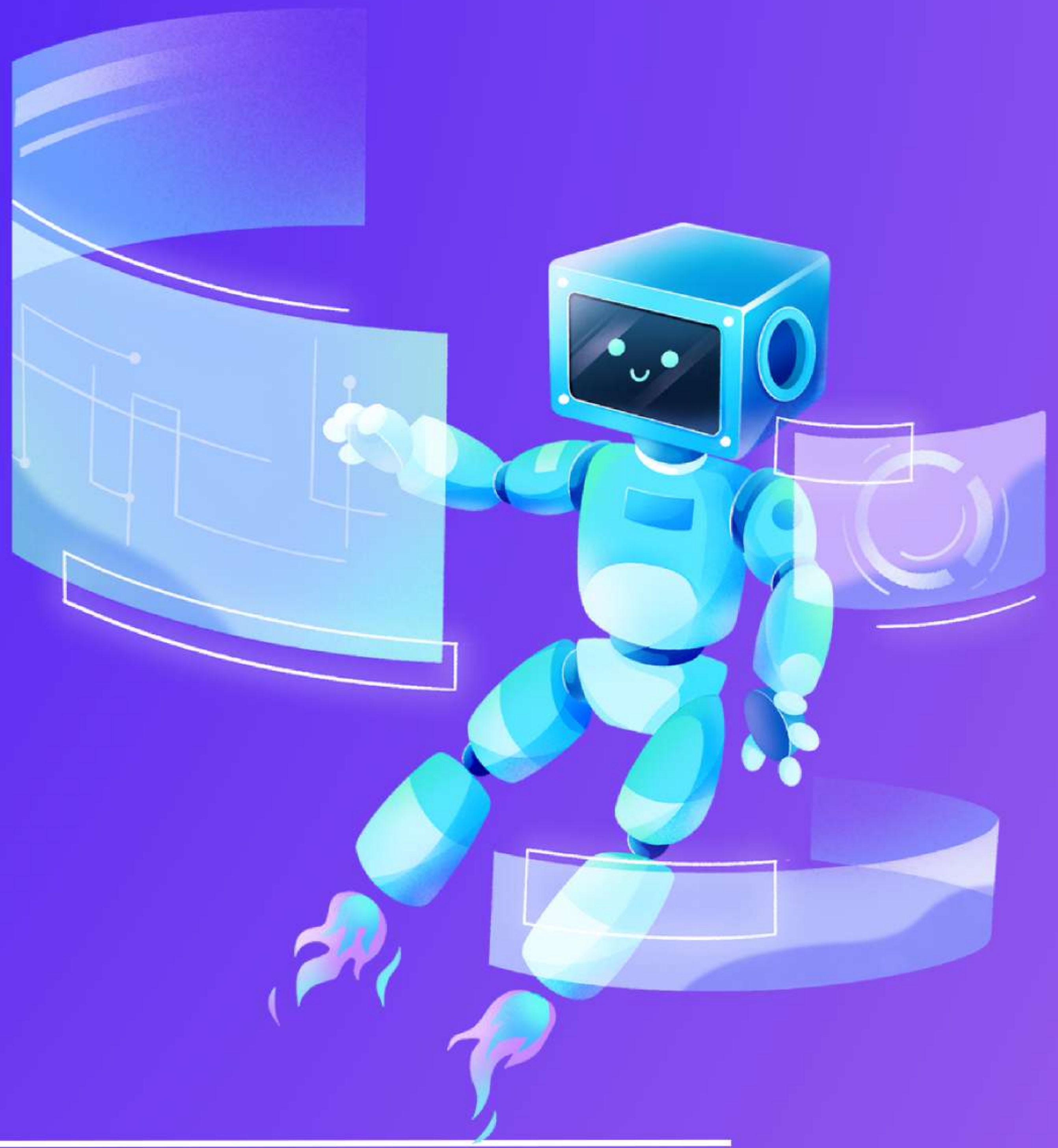
Definition

Planning in artificial intelligence (AI) refers to the process of generating a sequence of actions to achieve a goal or solve a problem in a given environment. It involves analyzing the current state, determining the desired outcome, and devising a series of actions to transition from the current state to the goal state efficiently.

Importance

Planning plays a crucial role in various real-world applications, such as robotics, logistics, and decision-making systems. In robotics, for example, a robot needs to plan its movements to navigate a cluttered environment and accomplish tasks efficiently. Similarly, in logistics, planning is essential for optimizing routes and schedules to minimize costs and maximize efficiency.

INTRODUCTION TO PLANNING IN AI



A Brief Overview

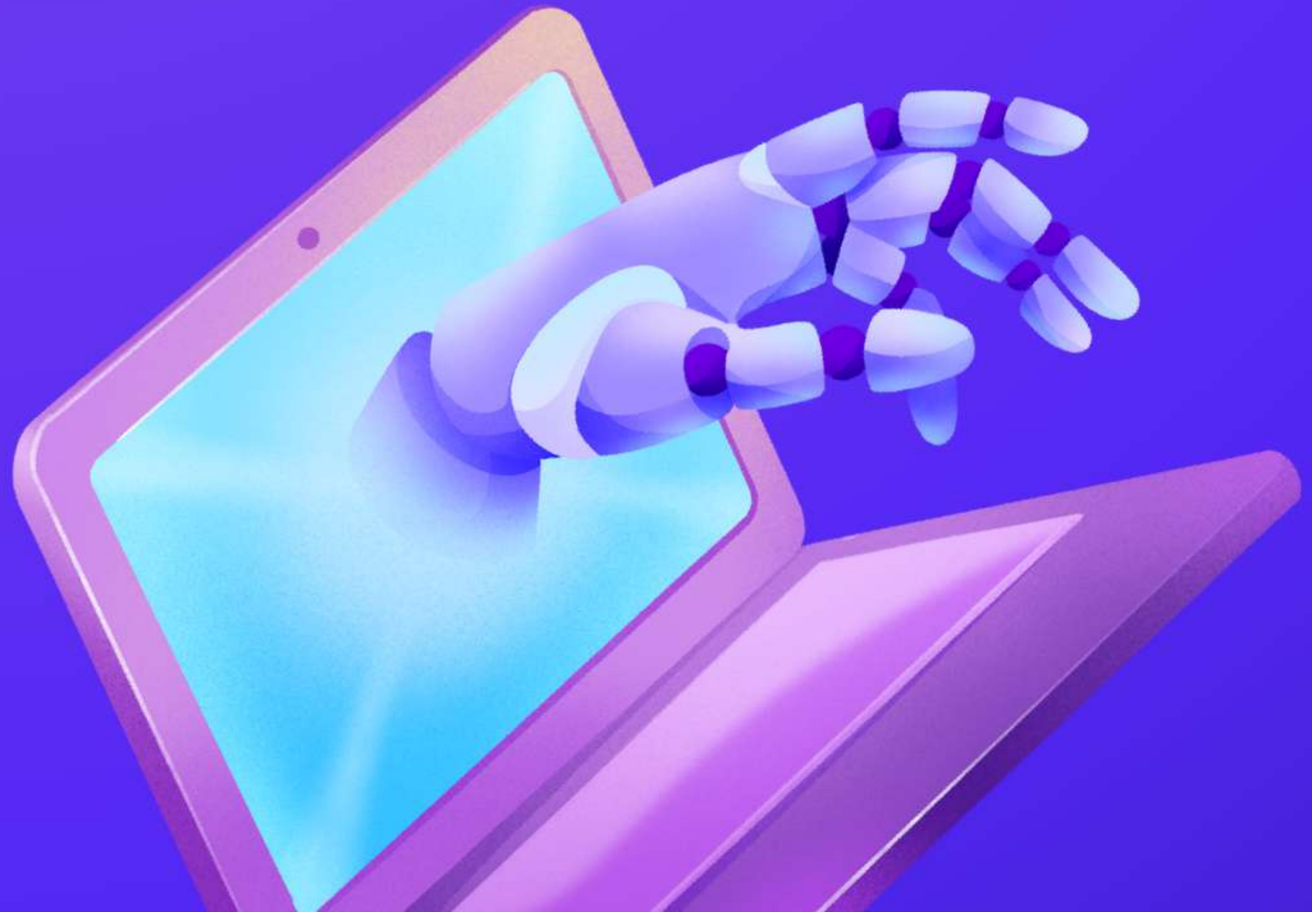
Deterministic planning assumes that the outcome of actions is predictable and consistent. In deterministic planning, the effects of actions are known and do not change over time or with repeated execution.

Non-deterministic planning, on the other hand, deals with environments where the outcome of actions is uncertain or probabilistic. In such environments, the effects of actions may vary depending on factors that are not under the planner's control, such as external events or the actions of other agents.

UNDERSTANDING NON-DETERMINISTIC DOMAINS

Characteristics

- **Uncertainty:** Actions may lead to different outcomes with varying probabilities.
- **Probabilistic Effects:** The effects of actions are influenced by probabilistic factors.
- **Partial Observability:** The planner may have incomplete information about the current state of the environment.



Definition

- Non-deterministic domains refer to environments or systems where the outcome of actions is uncertain or probabilistic. Unlike deterministic domains where actions lead to predictable outcomes, non-deterministic domains introduce variability and uncertainty into the planning process. In these domains, multiple possible outcomes may result from the same action, and the likelihood of each outcome may vary.

Examples

1. Autonomous Driving: In autonomous driving, unexpected events such as sudden changes in traffic conditions or the behavior of other vehicles introduce uncertainty into the planning process.
2. Healthcare Decision-Making: Medical diagnosis and treatment planning involve uncertainty due to factors such as variability in patient response to treatment and incomplete medical information.
3. Financial Markets: Decision-making in financial markets is affected by unpredictable market fluctuations and the actions of other market participants.

CHALLENGES POSED BY NON- DETERMINISM

01

Uncertainty Management:

Non-deterministic environments require planners to account for uncertainty in their decision-making process, which adds complexity to the planning algorithms.

02

Computational Complexity:

Handling uncertainty often involves considering multiple possible outcomes and their associated probabilities, leading to increased computational complexity.

03

Robustness and Adaptability:

Planners must develop strategies that are robust and adaptable to cope with unexpected events and uncertain outcomes.

04

Learning from Experience:

Non-deterministic planning may involve learning from past experiences and updating plans based on new information or observations.

APPROACHES TO MODELING NON-DETERMINISTIC DOMAINS

STOCHASTIC PLANNING

In stochastic planning, uncertainty is modeled explicitly using probability distributions to represent the likelihood of different outcomes. This approach considers the stochastic nature of the environment and incorporates probabilistic information into the planning process. Stochastic planning algorithms generate plans that optimize expected outcomes based on probabilistic models of the environment.

NON-DETERMINISTIC PLANNING

Non-deterministic planning, on the other hand, addresses uncertainty by considering multiple possible outcomes for each action. Unlike stochastic planning, which assigns probabilities to outcomes, non-deterministic planning explores all possible outcomes and selects actions that maximize utility or achieve goals under uncertainty.

PROBABILISTIC MODELS FOR REPRESENTING UNCERTAINTY

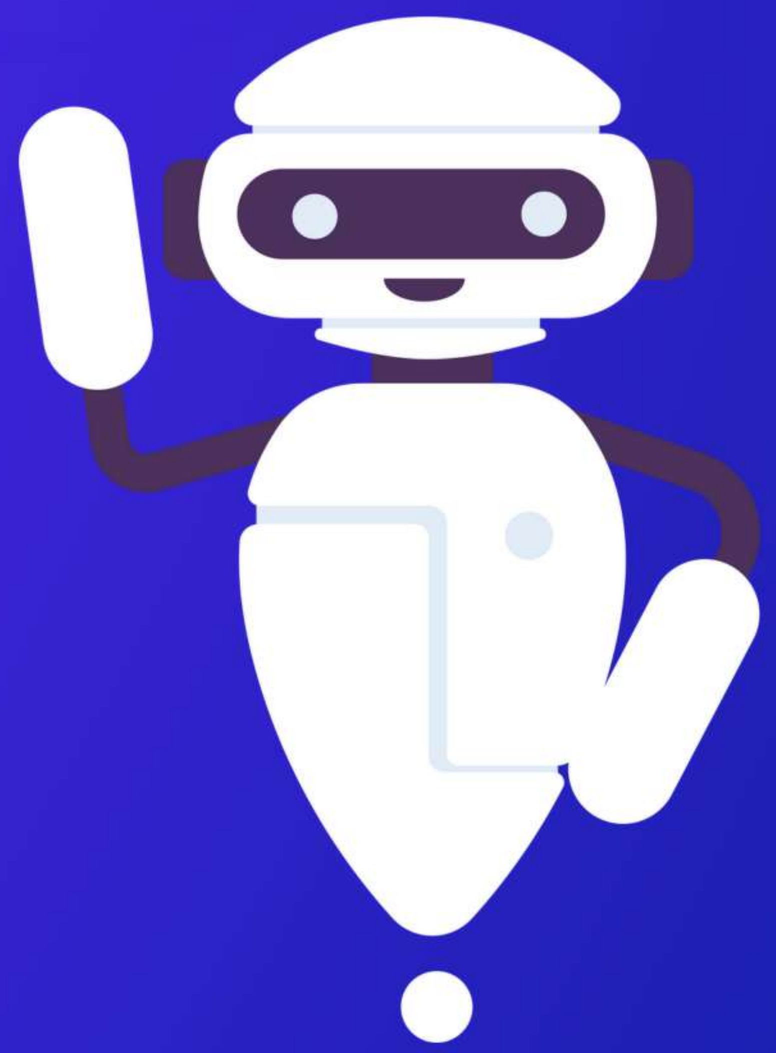
Probabilistic models are used to represent uncertainty in non-deterministic domains. These models capture the likelihood of different outcomes for actions or events in the environment. Common probabilistic models include:

- <u>Bayesian Networks:</u> Bayesian networks represent probabilistic dependencies among variables using directed acyclic graphs. They are widely used for modeling uncertain relationships and making probabilistic inferences.
- <u>Hidden Markov Models (HMMs):</u> HMMs are probabilistic models used to model sequences of observations where the underlying states are hidden or unobservable. They are often applied in sequential decision-making tasks with uncertain outcomes.
- <u>Probabilistic Graphical Models (PGMs):</u> PGMs are a general framework for representing and reasoning with uncertain knowledge. They combine graphical structures with probability theory to model complex dependencies and uncertainty in a compact and efficient manner.

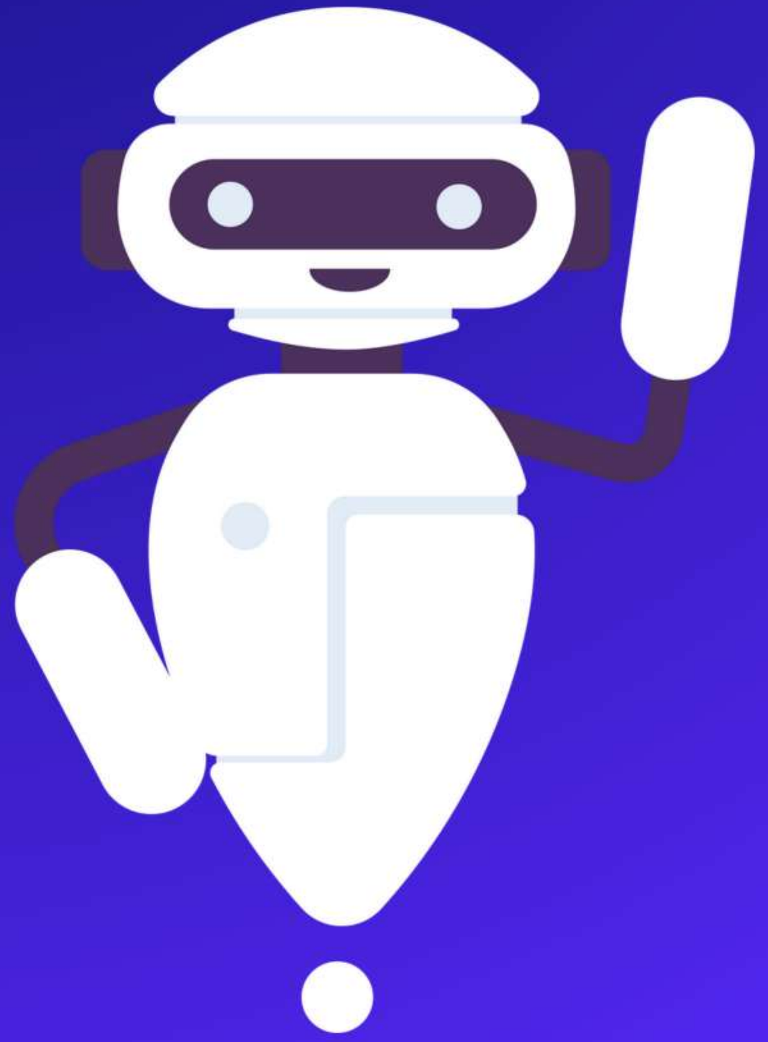
MARKOV DECISION PROCESSES (MDPS) AND THEIR APPLICATIONS IN PLANNING

Markov Decision Processes (MDPs) are mathematical frameworks used to model sequential decision-making under uncertainty. An MDP consists of a set of states, a set of actions, transition probabilities between states, and immediate rewards associated with state-action pairs. MDPs are characterized by the Markov property, which states that the future state depends only on the current state and action, independent of the past.

MDPs are widely used in planning and decision-making tasks where uncertainty is present. They provide a formal framework for modeling non-deterministic environments and designing optimal policies to achieve specified goals. MDP-based planning algorithms, such as value iteration and policy iteration, are used to compute optimal policies that maximize expected rewards or utility over time.



ALGORITHMS FOR NON-DETERMINISTIC PLANNING



Classical planning algorithms, such as A* (A-star) and BFS (Breadth-First Search), are widely used in deterministic environments where the outcome of actions is predictable. These algorithms search through the space of possible plans to find an optimal solution based on predefined heuristics or search strategies.

However, classical planning algorithms have limitations when applied to non-deterministic domains:

- Lack of Uncertainty Handling: Classical algorithms assume deterministic outcomes for actions and do not explicitly model uncertainty, making them unsuitable for non-deterministic environments.
- Incomplete Solutions: In non-deterministic domains, classical algorithms may fail to find optimal or even feasible solutions due to the inability to account for uncertain outcomes and their associated probabilities.

INTRODUCTION TO ALGORITHMS SPECIFICALLY DESIGNED FOR NON-DETERMINISTIC ENVIRONMENTS

MONTE CARLO TREE SEARCH (MCTS)

MCTS is a probabilistic search algorithm that uses random sampling to explore the search space. It is particularly well-suited for non-deterministic environments where the outcome of actions is uncertain. MCTS has been successfully applied in various domains, including games, robotics, and planning under uncertainty.

UPPER CONFIDENCE BOUNDS FOR TREES (UCT)

UCT is a variant of MCTS that incorporates an exploration-exploitation trade-off based on upper confidence bounds. It balances between exploring new actions and exploiting the best-known actions to improve decision-making in uncertain environments.

COMPARISON OF DIFFERENT ALGORITHMIC APPROACHES IN TERMS OF EFFICIENCY AND EFFECTIVENESS

The effectiveness and efficiency of algorithms for non-deterministic planning depend on various factors, including the nature of the environment, the level of uncertainty, and the complexity of the planning problem. Some key considerations for comparing different algorithmic approaches include:

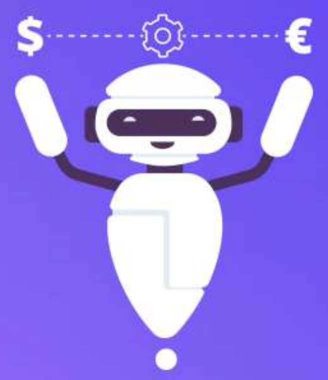
* Scalability: The ability of an algorithm to scale to large problem instances and handle complex decision-making tasks efficiently.
* Robustness: The ability of an algorithm to adapt to changes in the environment and cope with uncertainty and variability effectively.
* Optimality: The ability of an algorithm to find optimal solutions or approximate them within a reasonable computational budget.

HANDLING UNCERTAINTY IN PLANNING

TECHNIQUES FOR HANDLING UNCERTAINTY IN PLANNING ALGORITHMS

PROBABILISTIC MODELS

Incorporating probabilistic models to represent uncertain outcomes of actions and events. These models can include probability distributions or uncertainty estimates associated with different states and actions.



STOCHASTIC SEARCH

Using stochastic search algorithms that explore the space of possible plans by considering probabilistic outcomes of actions. These algorithms sample from probabilistic distributions to guide the search process.

MONTE CARLO SIMULATION

Employing Monte Carlo simulation techniques to estimate the expected value of different actions under uncertainty. By simulating multiple possible outcomes, planners can assess the robustness and effectiveness of candidate plans.

UNCERTAINTY-AWARE HEURISTICS

Designing heuristics that explicitly consider uncertainty in evaluating and selecting actions during the planning process. These heuristics can guide the search towards actions that minimize risk or maximize expected utility.

SENSING AND ACTING IN UNCERTAIN ENVIRONMENTS

1. Adaptive Sensing: Utilizing adaptive sensing techniques to gather information about the environment and update the planner's beliefs or probabilistic models in real-time. Adaptive sensing allows planners to make informed decisions based on the most up-to-date information available.

2. Risk-aware Decision-making: Incorporating risk-aware decision-making strategies that balance between exploration and exploitation in uncertain environments. These strategies consider both the potential rewards and risks associated with different actions, aiming to maximize expected utility while minimizing potential negative outcomes.

3. Online Planning: Implementing online planning algorithms that continuously update plans and actions based on real-time feedback and observations. Online planning enables systems to adapt and react to changing environmental conditions and unexpected events dynamically.

BAYESIAN APPROACHES TO PLANNING UNDER UNCERTAINTY

1. Bayesian Inference: Applying Bayesian inference techniques to update beliefs and estimate the posterior distribution of states and actions based on observed evidence. Bayesian inference allows planners to incorporate prior knowledge and new observations to make informed decisions under uncertainty.

2. Bayesian Decision Theory: Using Bayesian decision theory to compute optimal policies that maximize expected utility or minimize expected costs under uncertainty. Bayesian decision theory provides a principled framework for decision-making under uncertainty, taking into account both the uncertainty in the environment and the preferences of the decision-maker.

3. Bayesian Reinforcement Learning: Employing Bayesian reinforcement learning algorithms to learn optimal policies from interactions with the environment under uncertainty. These algorithms use Bayesian updates to update the policy and value functions based on observed rewards and states, enabling agents to adapt to uncertain and dynamic environments over time.

REAL-WORLD APPLICATIONS

ROBOTICS AND AUTONOMOUS SYSTEMS

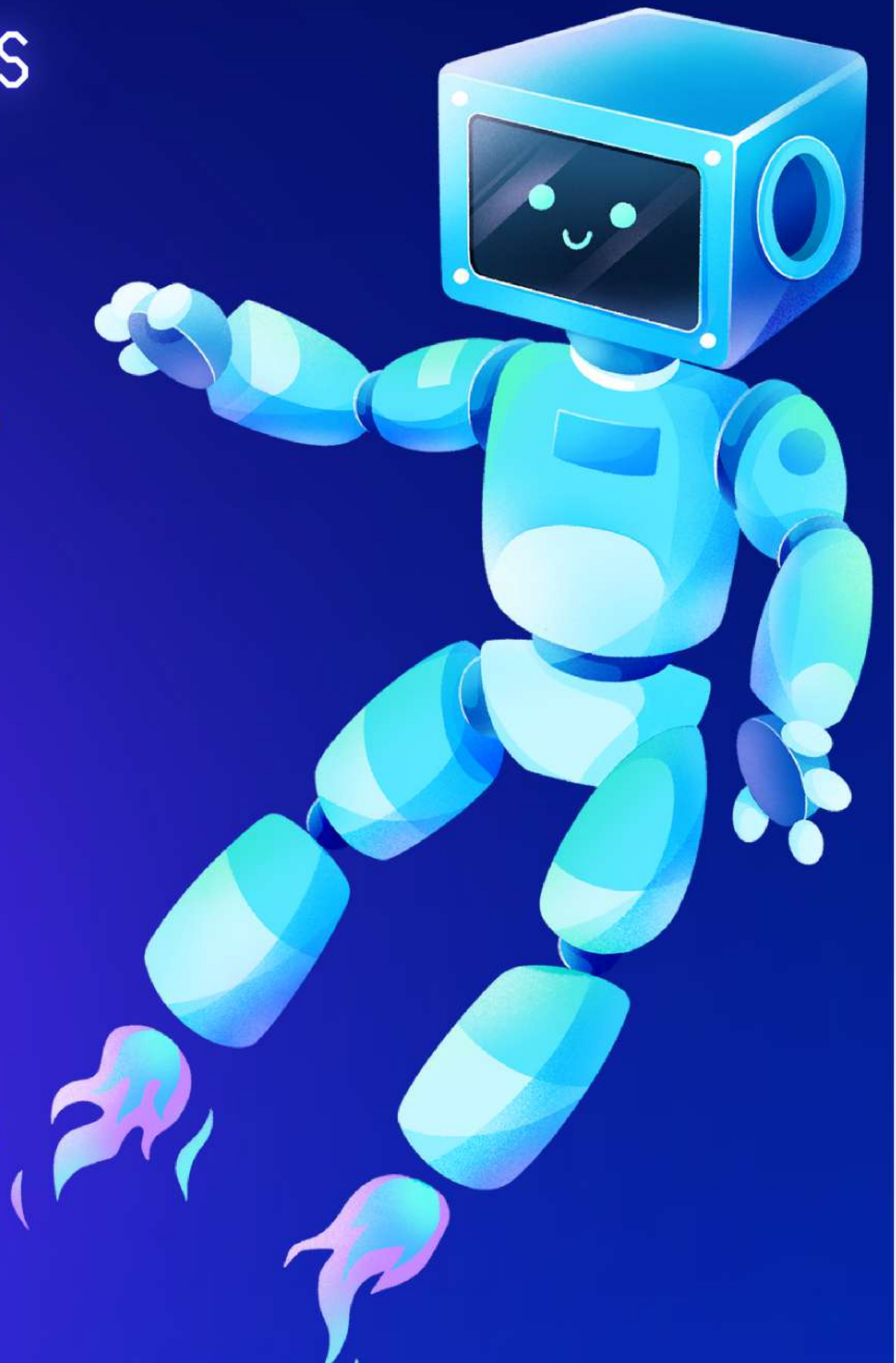
- Autonomous Navigation: Robots operating in dynamic environments, such as warehouses or urban areas, require non-deterministic planning to navigate obstacles, avoid collisions, and reach their destinations safely.

- Manipulation Tasks: Robots performing manipulation tasks in unstructured environments, such as picking objects from cluttered spaces or interacting with humans, utilize non-deterministic planning to account for uncertainties in object poses and environmental conditions.

HEALTHCARE MANAGEMENT

- Treatment Planning: Medical decision support systems employ non-deterministic planning to assist clinicians in devising personalized treatment plans for patients. These systems consider uncertainties in patient responses to treatments, disease progression, and available resources.

- Resource Allocation: Hospital management systems use non-deterministic planning to allocate medical resources, such as hospital beds, staff schedules, and medical supplies, to optimize patient care and operational efficiency.



REAL-WORLD APPLICATIONS

RESOURCE ALLOCATION AND SCHEDULING

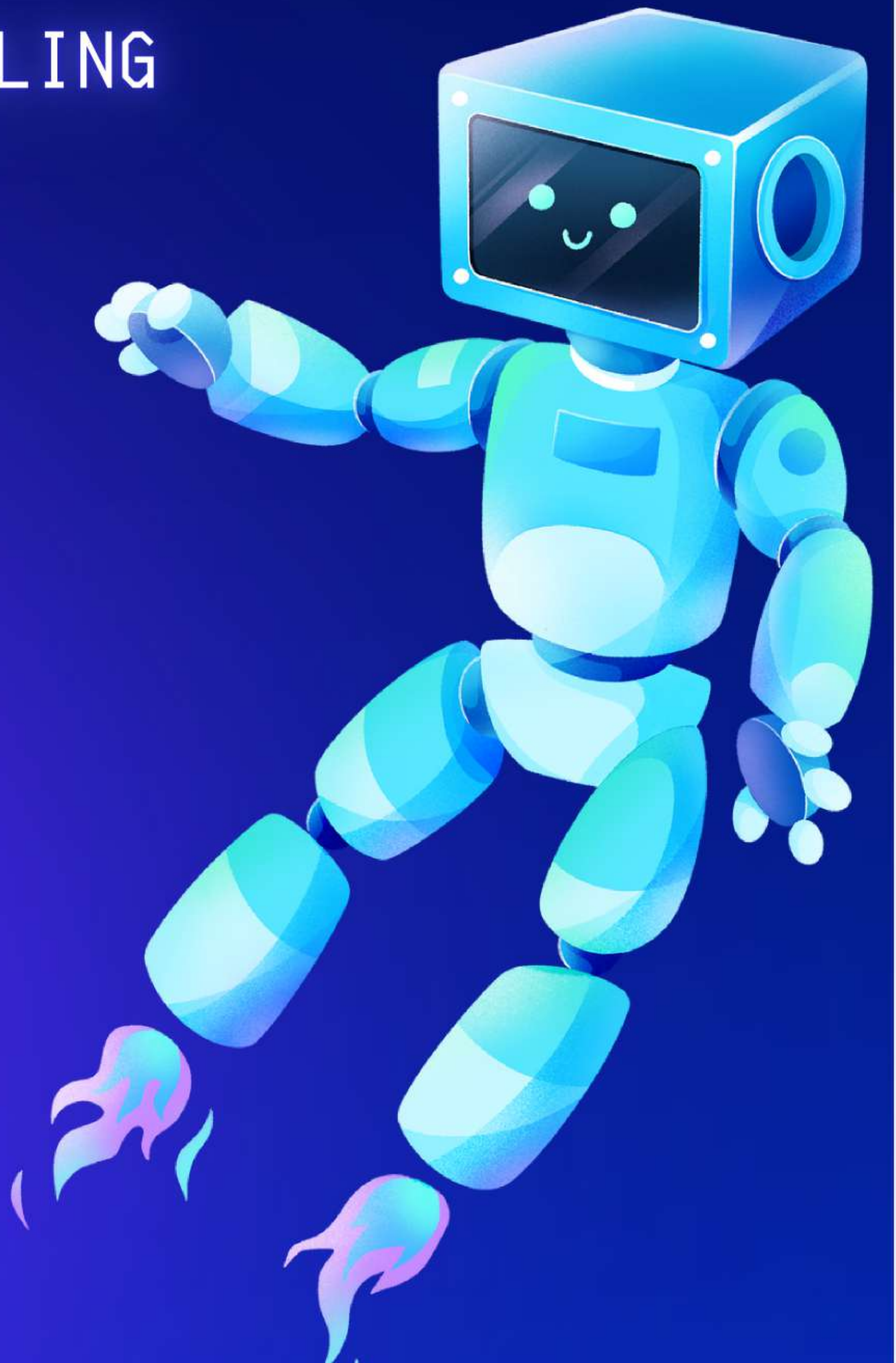
- Project Management: Non-deterministic planning is applied in project management to schedule tasks, allocate resources, and manage dependencies in complex projects with uncertain durations, resource availability, and task dependencies.

- Supply Chain Management: Logistics companies use non-deterministic planning to optimize supply chain operations, including inventory management, transportation scheduling, and demand forecasting, in dynamic and uncertain environments.

TRANSPORTATION AND LOGISTICS

- Route Planning: Transportation companies utilize non-deterministic planning to optimize route planning and scheduling for vehicles, considering factors such as traffic congestion, weather conditions, and unexpected delays.

- Freight Logistics: Logistics companies employ non-deterministic planning to optimize the movement of goods and cargo through global supply chains, considering uncertainties in transportation costs, delivery times, and demand fluctuations.



CHALLENGES FACED IN UNCERTAIN ENVIRONMENTS

Computational Complexity: Non-deterministic planning problems often involve large search spaces and complex decision-making processes, leading to computational challenges in finding optimal solutions within reasonable time frames

Uncertainty Modeling: Accurately modeling uncertainties in real-world domains, such as healthcare and logistics, remains a challenge due to the complexity of the underlying processes and the lack of complete information.

Integration with Existing Systems: Integrating non-deterministic planning solutions into existing workflows and systems can be challenging, requiring seamless interoperability and adaptation to diverse operational environments.

SUCCESS STORIES IN UNCERTAIN ENVIRONMENTS

Increased Efficiency: Implementing non-deterministic planning solutions has led to increased efficiency and cost savings in various industries, such as transportation, healthcare, and manufacturing.

Improved Decision-Making: Non-deterministic planning tools have empowered decision-makers to make informed decisions under uncertainty, leading to better resource allocation, risk management, and performance optimization.

Enhanced Robustness: Non-deterministic planning solutions have improved the robustness and adaptability of autonomous systems, such as robots and unmanned aerial vehicles, enabling them to operate effectively in dynamic and unpredictable environments.

AN ALGORITHMIC OVERVIEW

MONTE CARLO TREE SEARCH

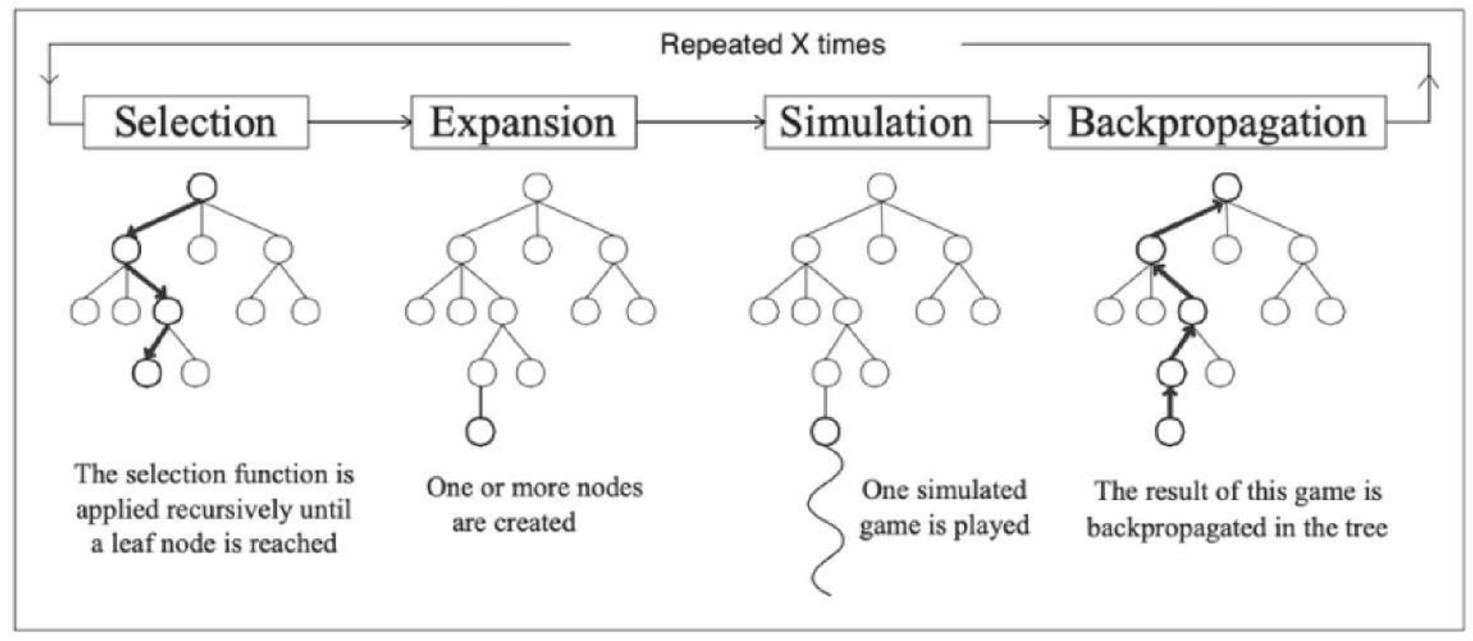


Figure 1: Outline of a Monte-Carlo Tree Search.

1. Initialization:
   1.1 Initialize a search tree with a single root node representing the current state of the problem.

2. Selection:
   2.1 Traverse the tree from the root node to a leaf node using a selection policy (e.g., Upper Confidence Bound) until reaching an unexplored or terminal state.

3. Expansion:
   3.1 Expand the selected leaf node by adding child nodes corresponding to possible actions from that state.

4. Simulation (Rollout):
   4.1 Perform a Monte Carlo simulation (rollout) from each newly expanded child node until reaching a terminal state.
   4.2 During the simulation, apply a rollout policy (e.g., random actions or a simple heuristic) to select actions until reaching a terminal state.

5. Backpropagation:
   5.1 Update the statistics of each visited node along the path from the root to the leaf based on the outcome of the simulation.
   5.2 Propagate the rewards obtained during the simulation back up the tree to update the statistics of ancestor nodes.

6. Action Selection:
   6.1 After a predefined number of simulations or time limit, select the action with the highest expected reward based on the statistics accumulated during the search.

UCT ALGORITHM

$$UCT_j = X_j + C * \sqrt{\frac{ln(n)}{n_j}}$$

1. Initialization:
   1.1 Initialize a search tree rooted at the current state.
   1.2 Each node in the tree represents a state in the search space, and each edge represents an action leading to a child state.

2. Selection:
   2.1 Traverse the tree from the root node to a leaf node using a selection policy, such as the Upper Confidence Bound (UCB) formula.
   2.2 At each level of the tree, select the child node that maximizes the UCB score, balancing between exploitation (choosing nodes with high expected rewards) and exploration (choosing nodes with uncertain outcomes).

3. Expansion:
   3.1 If the selected leaf node is not a terminal state, expand it by generating child nodes corresponding to possible actions from that state.

4. Simulation:
   4.1 Perform a Monte Carlo simulation (rollout) from each newly expanded child node until reaching a terminal state.
   4.2 During the simulation, apply a rollout policy (e.g., random actions or a simple heuristic) to select actions until reaching a terminal state.

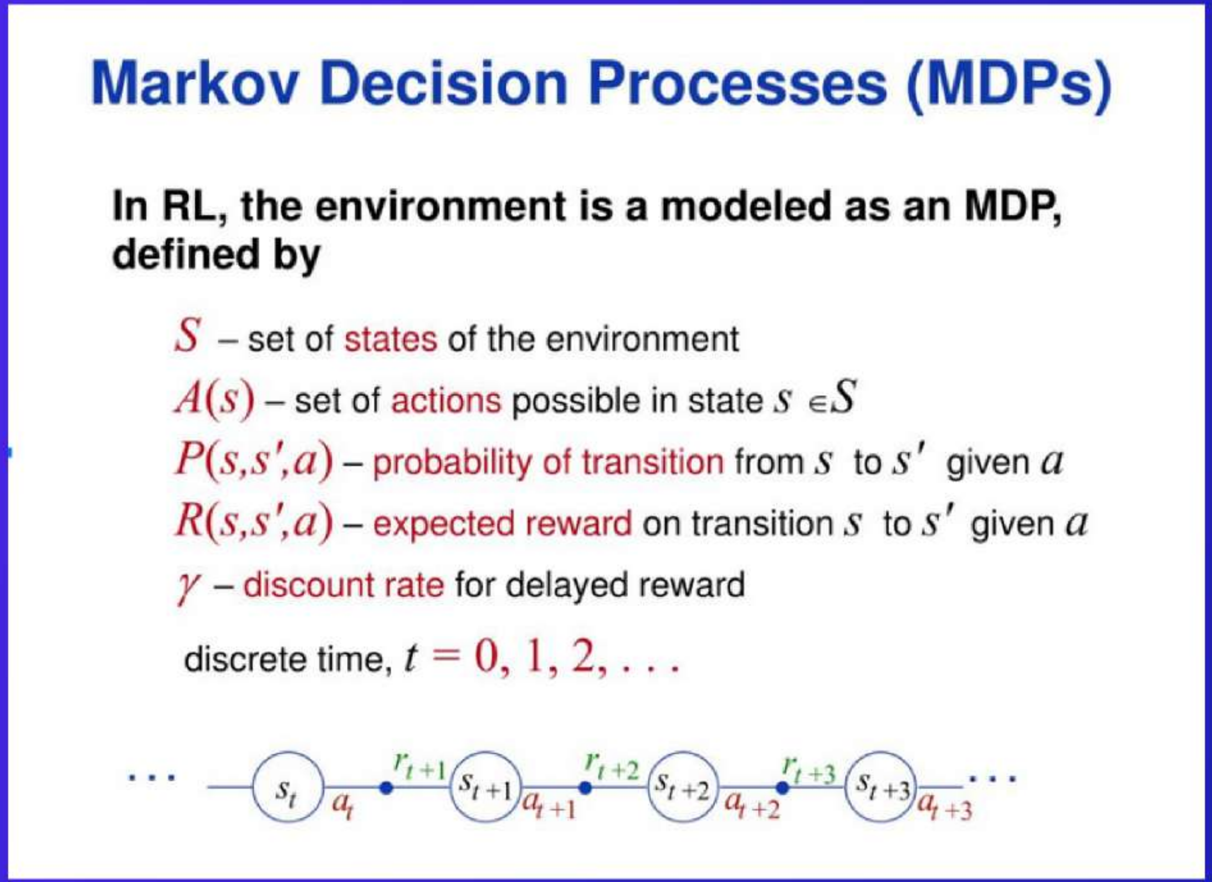
5. Backpropagation:
   5.1 Update the statistics of each visited node along the path from the root to the leaf based on the outcome of the simulation.
   5.2 Update the visit count and total reward of each node.
   5.3 Propagate the rewards obtained during the simulation back up the tree to update the statistics of ancestor nodes.

6. Action Selection:
   6.1 After a predefined number of simulations or time limit, select the action with the highest expected reward based on the statistics accumulated during the search.

MARKOV DECISION PROCESSES

1. Initialization:
   - Initialize the value function (V(s)) arbitrarily for all states (s) in the MDP.

2. Value Iteration:
   - Repeat until convergence:
     - For each state (s) in the MDP:
       - Calculate the new value of the state using the Bellman optimality equation:
         [V(s) ← max_asum_{s', r} P(s', r|s, a) < [r + gamma V(s')]]
       - where:
         - (a) represents the available actions in state (s),
         - (P(s', r|s, a)) is the transition probability function,
         - (r) is the immediate reward,
         - (gamma) is the discount factor,
         - (V(s')) is the value of the next state (s') after taking action (a).



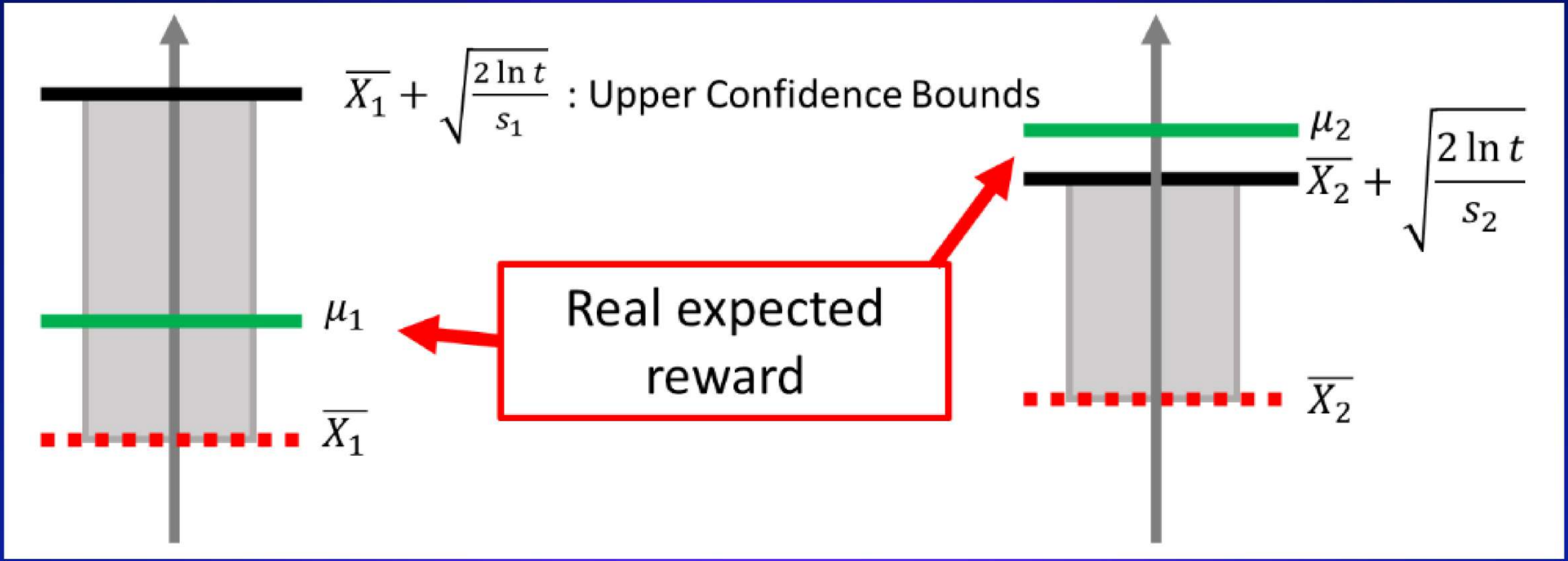
3. Policy Extraction:
   - Once the value function has converged, extract the optimal policy (pi^*(s)) from the value function:
     [pi^*(s) = {argmax}_a \sum_{s', r} P(s', r|s, a) left[r + gamma V(s') right]]

This algorithm iteratively updates the value function of each state until convergence, based on the expected immediate rewards and future values of successor states. Once the value function converges, the optimal policy can be extracted by selecting the action that maximizes the expected cumulative reward for each state.

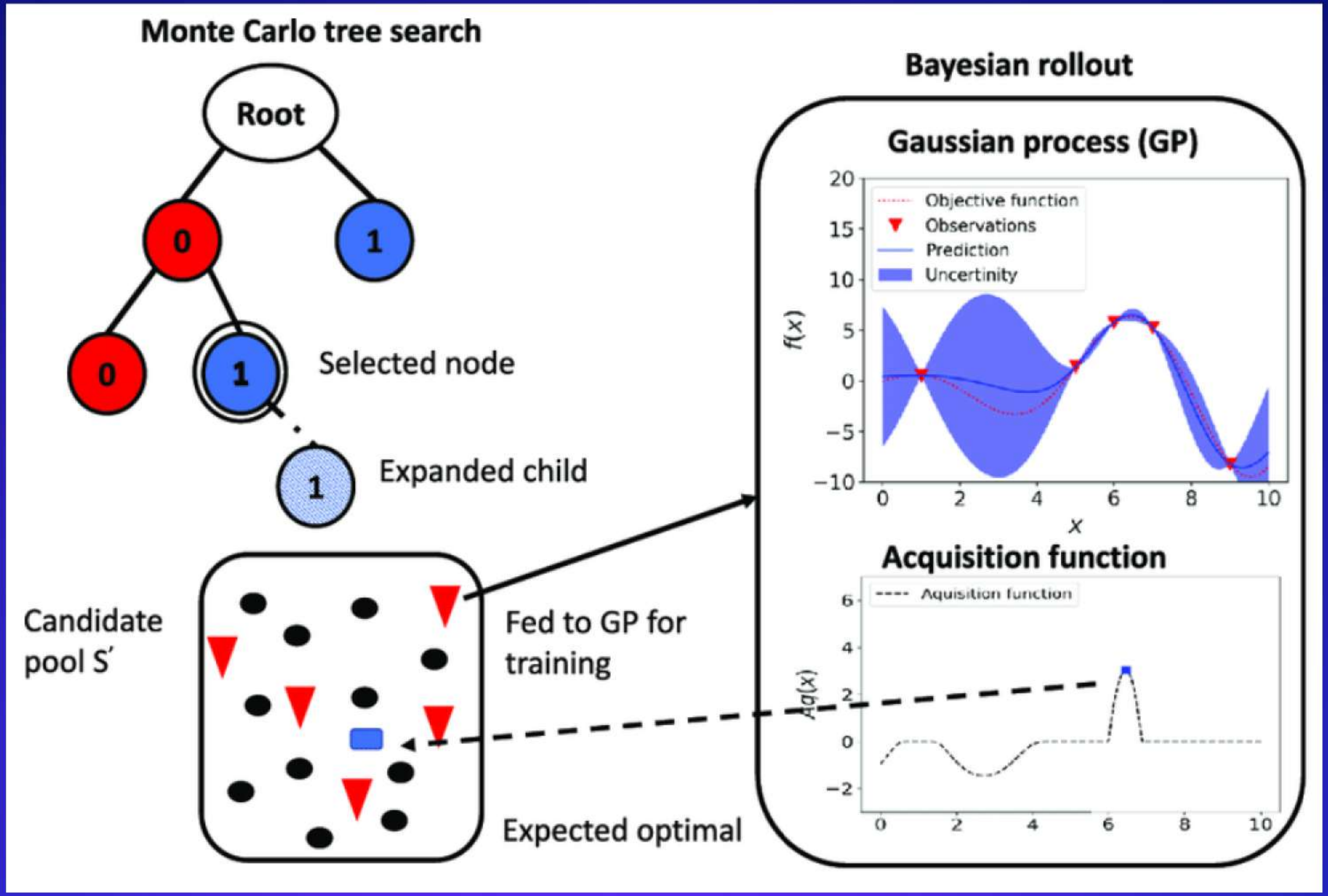
Note: The above algorithm assumes a finite MDP with known transition probabilities and rewards. For continuous or partially observable MDPs, alternative methods such as reinforcement learning algorithms may be used.

AN ARCHTECTURAL OVERVIEW

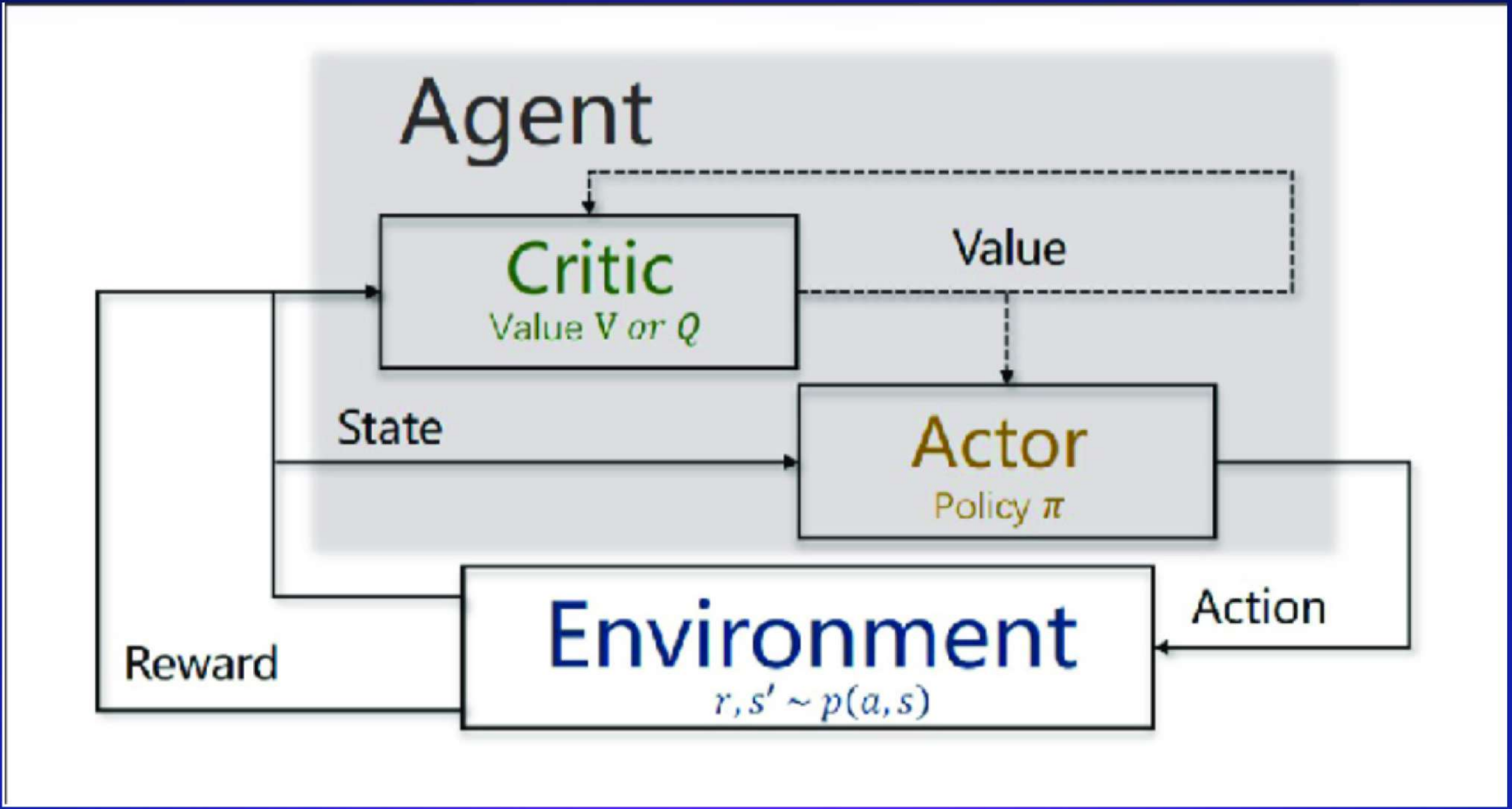
UCT ARCHITECTURE



MONTE CARLO TREE SEARCH ARCHITECTURE



MARKOV DECISION PROCESS ARCHITECTURE



FUTURE DIRECTIONS AND RESEARCH CHALLENGES

1. **Deep Learning for Uncertainty Modeling:** T he integration of deep learning techniques with non-deterministic planning algorithms offers promising avenues for improving uncertainty modeling and decision-making in complex and uncertain environments. Deep learning models can learn representations of uncertainty from data and provide more accurate estimates for probabilistic outcomes.

2. **Multi-Agent Planning:** With the proliferation of autonomous systems and multi-agent environments, there is growing interest in developing non-deterministic planning algorithms capable of coordinating and interacting with multiple agents effectively. Research in this area focuses on decentralized decision-making, coordination strategies, and negotiation protocols to address challenges in multi-agent planning.

3. **Human-Robot Interaction:** Non-deterministic planning plays a crucial role in enabling robots to interact and collaborate with humans in real-world settings. Future research aims to develop planning algorithms that can understand and adapt to human intentions, preferences, and behaviors, facilitating seamless human-robot interaction in various domains, including assistive robotics, healthcare, and collaborative manufacturing.

OPEN RESEARCH QUESTIONS AND CHALLENGES IN THE FIELD

01

- **Scalability and Efficiency**: Non-deterministic planning algorithms often face scalability challenges when applied to large-scale problems with complex uncertainties. Research is needed to develop scalable algorithms that can handle large search spaces and high-dimensional state and action spaces efficiently while maintaining optimality or near-optimality.

02

- **Robustness to Model Uncertainty**: Current non-deterministic planning approaches rely on probabilistic models to represent uncertainty. However, uncertainties in real-world domains are often complex and difficult to model accurately. Addressing the challenge of robustness to model uncertainty requires developing algorithms that can adapt to incomplete or inaccurate models and make robust decisions under uncertainty.

POTENTIAL ADVANCEMENTS AND APPLICATIONS ON THE HORIZON

01

- **Autonomous Systems and Robotics:** Advancements in non-deterministic planning are expected to drive progress in autonomous systems and robotics, enabling robots to operate autonomously in dynamic and uncertain environments, such as disaster response, search and rescue, and exploration missions.

02

- **Healthcare and Personalized Medicine:** Non-deterministic planning algorithms hold promise for revolutionizing healthcare delivery and personalized medicine by enabling tailored treatment planning, resource allocation, and decision support systems that account for patient-specific factors, uncertainties, and variability.

THANK YOU!

References

Reference - 1
Reference - 2
Reference - 3