

AI - 7-Dec 2025

# A SSIGNMENT 04

Khadija Jumani

SP23-BDS-023

- Title : Planning Under Uncertainty!

## 1. Introduction :-

Modern AI systems frequently operate in environments where outcomes are uncertain due to incomplete information, noisy sensors, unpredictable actions, or stochastic events. Planning under uncertainty helps intelligent agents decide optimal actions despite these challenges!

Three major approaches are widely used:

### a) Classical Planning:

Deterministic, Complete Information and predictable action outcomes.

### b) Probabilistic Planning:

Uncertain outcomes modeled using probabilities

(Bayesian Networks, Hidden Markov Models, MDPs).

c) Planning in Nondeterministic Domains:

Actions may have multiple possible outcomes; includes sensor-less planning, contingent planning and online planning.

→ This report compares these planning strategies across two-real-world AI applications:

1. Autonomous Robot Navigation in Unknown Environments.

2. Medical Diagnosis and Treatment Recommendation Systems.

→ Each application contains inherent uncertainty, making it ideal for comparative analysis.

P.T.O

## 2. Application 1 : Autonomous Robot Navigation :

### 2.1 Description of Application :

A delivery or service robot must move from a starting point to a target location while avoiding obstacles, handling noisy sensors, uncertain wheel movements, and dynamic environments.

Robot navigation uncertainty arises from:

- Sensor noise (LIDAR, ultrasonic sensors)
- Inaccurate localization
- Dynamic obstacles (humans, moving objects)
- Actuator errors (slippery floor, wheel drift)
- Partial observability of maps.

### 2.2 How classical Planning Handles Robot Navigation :

#### → Classical Planning Characteristics

- Requires a complete and deterministic map.
- Uses algorithms like A\*, Dijkstra, Forward Search, or Backward State-Space Search.

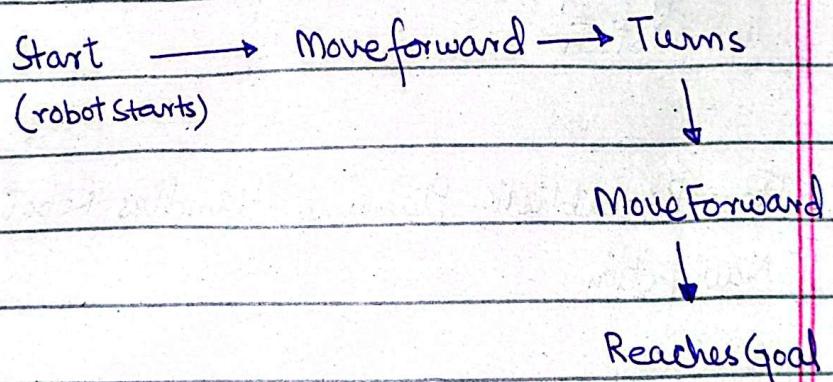
#### → Performance

- Works well in static and known environments.

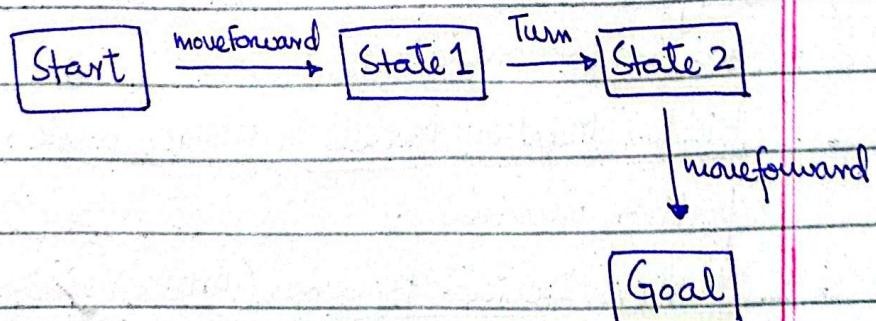
- Fails when sensors are noisy or when an unexpected obstacle appears.
- No mechanism to deal with uncertain action outcomes (e.g. # wheel slips).

→ Diagrams (ASCII Diagrams) :-

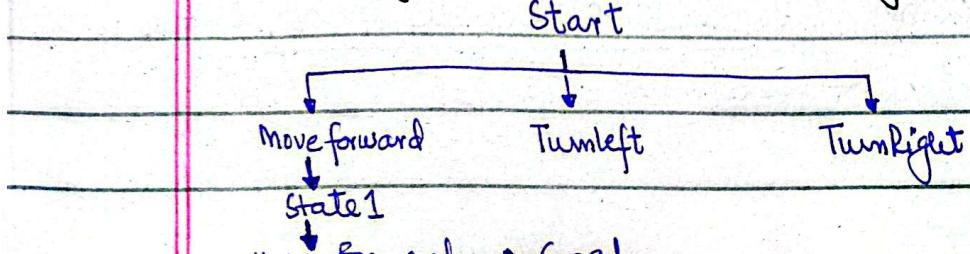
- Classical Planning Action Sequence :



- More Detailed Version (State-Space Path):



- Tree Diagram of Classical Planning:



## → What Diagrams Represents :

This Diagram shows how a classical planner (like A\*, DFS, BFS, Forward Search) navigates from a starting point to a goal step by step in a world where:

- ✓ Actions always succeed.
- ✓ The Environment is known.
- ✓ There is no uncertainty.
- ✓ Every step leads to a predictable new state.

## 2.3 How Probabilistic Planning Handles Robot Navigation

### → Probabilistic Methods

- Bayesian Networks model uncertain locations and sensor readings.
- Hidden Markov Models (HMMs) track robot position over time.
- Markov Decision Processes (MDPs) model uncertain action outcomes.
- POMDPs (Partially Observable MDPs) handle sensor + action uncertainty.

## → Performance :

- Can predict uncertainty in movement and perception.
- Provides optimal policies that maximize long-term success.
- Used in autonomous cars, drones, and SLAM (Simultaneous Localization and Mapping)

## → Probabilistic Diagram:

Location -t → Action → Location -t+1



## 2.4 Planning in Nondeterministic Domains

→ Sensor-less planning : Robot operates without reliable sensor feedback; assumes worst-case obstacles.

→ Contingent Planning : Robot uses if-else branching based on sensor readings.

IF sensor detects obstacle → turn left

ELSE → move forward.

→ Online Planning : Robot replans continually based on real-time data (Used in ROS navigation stack)

Performance :

- More adaptive than classical planning.
- Handles partial observability.
- Useful in dynamic environments.

### 2.5 Best Planning Strategy for Robot Navigation : (Comparative Analysis)

Approach	Strengths	Weakness
→ Classical	Fast, efficient, simple	Assumes perfect sensors & static map
→ Probabilistic	Handles noise, uncertainty, optimal	Computationally expensive
→ Non-deterministic	Adaptive, works with unknown environments	Requires frequent replanning.

Conclusion :

Probabilistic + Contingent planning hybrid  
performs best because robot navigation  
is inherently noisy and dynamic.

Most modern robots use POMDP + online  
replanning

### 3. Application 2 : Medical Diagnosis

#### 3.1 Description

- AI diagnoses diseases and recommends treatments.
- Uncertainty due to:
  - missing patient data
  - Variable symptoms
  - Test errors
  - Probabilistic disease occurrence
  - Different patient responses to treatment.

#### 3.2 Classical Planning

- Uses fixed rules (e.g. If fever+cough → flu)
- Limitations:
  - Can't handle uncertainty
  - Ignores test noise
  - Fails with overlapping symptoms.

#### 3.3 Probabilistic Planning

- Tools : Bayesian Networks, PGMs, HMMs.
- Strengths:
  - Models diseases probabilistically
  - Handles noisy/incomplete test data
  - More accurate diagnosis
- Treatment uses MDPs for best long-term actions.

### 3.4) Nondeterministic Planning

- Sensor-less : Used when data missing.
- Contingent : Plan depends on test results
- Online : Updates  
    ↓  
    treatment as new data arrives  
    (IF positive,  $\rightarrow A$   
    else  $\rightarrow B$ )

### 3.5) Best Strategy

- Probabilistic planning is best :
  - Handles uncertainty
  - Combines symptoms + tests accurately.

## 4. Comparative Summary

Method	Key Strength	Key Weakness
Classical	Simple	No uncertainty handling
Probabilistic	Most Accurate	High Computation
Nondeterministic	Adaptive	Limited alone

### → Overall Best :

- Robot Navigation : Probabilistic + Online
- Medical Diagnosis : Probabilistic (Bayesian)

## 5. Computational Trade-offs

- Classical : fast, low accuracy.
- Probabilistic : High accuracy, heavy computation.
- Nondeterministic : Moderate, real-time possible.

## 6. Hybrid Strategy :

Combine probabilistic reasoning +  
contingent branching + online  
updates for best results.

## 7. Conclusion :

- Classical planning fails in uncertain environments
- Probabilistic planning gives best decisions with noisy or incomplete data.
- Combining probabilistic + nondeterministic methods yields highest performance.

## 8. References (APA)

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