Representing Knowledge in an Uncertain Domain

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What is an uncertain domain in ai

An uncertain domain in artificial intelligence (AI) refers to a field or environment where the information available is incomplete, ambiguous, noisy, or inherently unpredictable. Unlike deterministic domains where outcomes can be predicted with certainty given the inputs, uncertain domains require AI systems to handle and reason about uncertainty in a structured manner.

Characteristics of uncertain domains

- **Incomplete Information:** The system does not have access to all the data required to make a fully informed decision.
- **Ambiguity:** Information might be unclear or open to multiple interpretations.
- **Noise:** Data might be corrupted or imprecise due to measurement errors or external factors.
- **Stochastic Processes:** The environment might involve random processes or events.

Importance of handling uncertainity

Accurately representing and reasoning about uncertain information is crucial for making reliable predictions and decisions. Handling uncertainty enables AI systems to:

- **Make informed decisions based on probabilistic reasoning.**
- **Adapt to new information and changing environments.**
- **Provide robust and reliable performance in complex scenarios.**

Representing knowledge in an uncertain domain

1. ***Probabilistic Reasoning***

   Probabilistic reasoning involves representing knowledge using probability theory to manage uncertainty. This approach is widely used in AI for tasks such as diagnosis, prediction, and decision-making under uncertainty.

Scenario: Predicting whether it will rain tomorrow based on today's cloudy sky.

Variables:
- R: It will rain tomorrow.
- C: The sky is cloudy today.

Probabilities:
- P(R) = 0.3 (30% chance of rain).
- P(C|R) = 0.8 (80% chance of cloudy skies if it will rain).
- P(C|¬R) = 0.2 (20% chance of cloudy skies if it won't rain).

Goal: Find P(R|C): Probability it will rain given that the sky is cloudy.

Steps:
1. Calculate P(C):
   P(C) = P(C|R) * P(R) + P(C|¬R) * P(¬R)
   P(C) = (0.8 * 0.3) + (0.2 * 0.7) = 0.38

2. Apply Bayes' Theorem:
   P(R|C) = (P(C|R) * P(R)) / P(C)
   P(R|C) = (0.8 * 0.3) / 0.38 ≈ 0.632

Conclusion: If the sky is cloudy today, there's about a 63.2% chance it will rain tomorrow.

2) Hidden Markov Models

Hidden Markov Models (HMMs) are used to model time series data where the system being modeled is assumed to be a Markov process with hidden states. HMMs are widely used in speech recognition, bioinformatics, and other sequential data applications.

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Applications: Speech recognition, bioinformatics, and other sequential data applications.

Example: Speech Recognition

States (hidden):
- S1: Silent
- S2: Voiced

Observations:
- O1: Low energy
- O2: High energy

Probabilities:
- Transition Probabilities:
  - P(S2|S1) = 0.6
  - P(S1|S1) = 0.4
  - P(S1|S2) = 0.3
  - P(S2|S2) = 0.7
- Emission Probabilities:
  - P(O1|S1) = 0.8
  - P(O2|S1) = 0.2
  - P(O1|S2) = 0.4
  - P(O2|S2) = 0.6

Scenario: Determine the most likely sequence of hidden states (Silent or Voiced) given a sequence of observed data (Low or High energy).

Steps:
1. Define the model parameters (transition and emission probabilities).
2. Use algorithms like Viterbi to find the most likely sequence of hidden states.

Conclusion: HMMs help in modeling and predicting sequences in time series data by considering hidden states and observed data.

3) Markov Decision Processes

Markov Decision Processes (MDPs) provide a framework for modeling decision-making in environments with stochastic dynamics. MDPs consist of states, actions, transition probabilities, and rewards, enabling the computation of optimal policies for decision-making.

EXAMPLE:-

States:

- S1: Start position
- S2: Intermediate position
- S3: Goal position

Actions:

- A1: Move forward
- A2: Turn left
- A3: Turn right

Transition Probabilities:

- P(S2|S1, A1) = 0.9 (90% chance of moving to S2 from S1 by moving forward)
- P(S1|S1, A2) = 0.1 (10% chance of staying in S1 when turning left)
- P(S3|S2, A1) = 0.8 (80% chance of reaching S3 from S2 by moving forward)

Rewards:

- R(S1, A1, S2) = 10 (Reward for moving from S1 to S2 by moving forward)
- R(S2, A1, S3) = 50 (Reward for moving from S2 to S3 by moving forward)

4) Fuzzy Logic

Fuzzy logic is an approach to reasoning that deals with approximate rather than fixed and exact values. Unlike traditional binary logic, fuzzy logic variables can have a truth value that ranges between 0 and 1, representing the degree of truth.

EXAMPLE:-

Traditional Logic:

- Cold: Temperature < 18°C (True or False)
- Hot: Temperature > 25°C (True or False)

Fuzzy Logic:

- Temperature can be Cold, Warm, or Hot with degrees of truth.
- Example for 22°C:
  - Cold: 0.2 (20% cold)
  - Warm: 0.7 (70% warm)
  - Hot: 0.1 (10% hot)

Fuzzy Sets:

- Cold: Defined with membership function.
- Warm: Defined with membership function.
- Hot: Defined with membership function.

Fuzzy Rules:

- If temperature is Cold, then set heater to High.
- If temperature is Warm, then set heater to Medium.
- If temperature is Hot, then set heater to Low

5) Case-Based Reasoning

Case-based reasoning (CBR) is an approach where past cases (experiences) are used to solve new problems. In uncertain domains, CBR can be combined with probabilistic methods to estimate the likelihood of various outcomes based on similar past cases.

For example, a medical diagnosis system uses past patient cases to predict likely diagnoses and treatment outcomes for new patients with similar symptoms and medical histories.

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- **Medical Diagnosis:** Probabilistic models like Bayesian networks are used to diagnose diseases.
- **Natural Language Processing:** HMMs and probabilistic context-free grammars are used for speech recognition and language modeling.
- **Robotics:** Robots use probabilistic reasoning to handle sensor noise and uncertain environments for navigation and manipulation tasks.

THANK YOU