Artificial Intelligence ADC503

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Chapter – 05

Reasoning Under Uncertainty

5		**Reasoning Under Uncertainty**
		Handling Uncertain Knowledge, Random Variables, Prior and Posterior Probability, Inference using Full Joint Distribution
		Bayes' Rule and its use, Bayesian Belief Networks, Reasoning in Belief Networks

Uncertainty

It refers to situations where there is a lack of complete information or knowledge about a particular aspect, leading to ambiguity and unpredictability.

- 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.
- sources of uncertainty in AI:

Random variables

- Random variables are a way to represent uncertainty in artificial intelligence (AI) by mapping the outcomes of a process to numerical values. They can be used to represent the outcome of an experiment that hasn't been performed yet, or a value that is currently uncertain.

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 Uncertainty

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

Strategies used to handle Uncertainty

1) Probabilistic Models
2) Bayesian Networks
3) Monte Carlo Methods
4) Decision Theory
5) Fuzzy Logic
6) Qualitative Reasoning

- **Probabilistic Models:** AI systems can incorporate probabilistic models to represent uncertainty. Instead of providing a single, deterministic answer, these models assign probabilities to different outcomes.
- **Uncertainty Quantification:** AI systems should be capable of quantifying uncertainty. This involves estimating the likelihood of different outcomes or the confidence level associated with a particular decision.
- **Continuous Learning and Adaptation:** AI systems should be able to adapt and improve over time by continuously learning from new data. This adaptive learning process can help AI models better cope with changing environments and evolving uncertainties.

1) Probabilistic reasoning

- It involves using probability theory to make decisions and draw conclusions based on uncertain or incomplete information.
- It's a way for AI systems to handle uncertainty and make educated guesses rather than giving definitive answers.For **Example:**
- AI weather app that uses probabilistic reasoning.
- When you check the app, it doesn't just give you a single weather forecast (e.g., "It will rain today"). Instead, it provides a probability-based forecast like this:
- "There's a 70% chance of rain today."
- "There's a 30% chance of sunshine."
- Instead of making binary (yes/no) decisions, AI acknowledges and quantifies uncertainty by expressing probabilities.
- For instance, it might say, "There's an 80% chance it's true," indicating the level of confidence in an outcome.

2) Bayesian Network

- Bayesian probability theory is a common framework used in probabilistic reasoning. It involves updating probabilities as new evidence becomes available.
- For example, if a medical test is 90% accurate and yields a positive result, Bayesian reasoning allows for adjusting the probability of having a disease based on this new information

Bayesian Network

- **Machine Learning:** In machine learning, it's used for Bayesian inference and probabilistic modeling. For instance, it's employed in Bayesian networks, which are graphical models that represent probabilistic relationships among variables.
- **Natural Language Processing:** Bayes' Theorem can be used in text classification tasks, such as spam detection, sentiment analysis, and language modeling.
- **Medical Diagnosis:** Bayes' Theorem helps doctors update the probability of a patient having a disease based on the results of medical tests and the patient's symptoms.

Bayesian Network

- **Autonomous Systems:** In autonomous systems like self-driving cars, Bayes' Theorem is used for sensor fusion and decision-making under uncertainty.
- **Recommendation Systems**: It can be applied in recommendation engines to improve the accuracy of personalized recommendations by updating user preferences based on their interactions and feedback.

3) Rule-based systems

- Rule-based systems use a set of conditional rules to make decisions or draw conclusions.
- These rules consist of conditions and corresponding actions.
- The system evaluates conditions and triggers actions based on the conditions that are satisfied.
- Example: In a weather forecasting system, a rule might be: If the sky is cloudy and the temperature is below 10°C, then predict rain.
- The system checks the conditions (cloudy sky and low temperature) and triggers the action (predicting rain) if both conditions are met.
- Bayesian Networks in AI

4) 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: An autonomous robot navigating a grid world can use an MDP to determine the optimal path to its destination while accounting for uncertain movements and rewards.**

5) 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.
- Fuzzy Sets and Membership Functions
- Fuzzy sets allow for the representation of concepts with vague boundaries. Each element in a fuzzy set has a membership value indicating its degree of belonging to the set.putation of optimal policies for decision-making.
- **Example: In a temperature control system, the concept of “warm” can be represented as a fuzzy set with a membership function assigning values between 0 (not warm) and 1 (completely warm) to different temperatures.**

Applications of Uncertain Knowledge Representation

- **Medical Diagnosis:** Probabilistic models like Bayesian networks are used to diagnose diseases based on symptoms and medical history.
- **Autonomous Vehicles:** Fuzzy logic and MDPs help autonomous vehicles navigate and make decisions in dynamic environments.
- **Natural Language Processing:** probabilistic context-free grammars are used for tasks like speech recognition and language modeling.
- **Robotics:** Robots use probabilistic reasoning to handle sensor noise and uncertain environments for navigation and manipulation tasks.
- **Finance:** Probabilistic models are employed for risk assessment, fraud detection, and market prediction.

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Probability (Cont.)

We can find the probability of an uncertain event by using the below formula.

$$\textbf{Probability of occurrence} = \frac{\text{Number of desired outcomes}}{\text{Total number of outcomes}}$$

- $P(\neg A)$ = probability of a not happening event.
- $P(\neg A) + P(A) = 1$.

Prior probability

- Prior probability is defined as the initial assessment or the likelihood of the event or an outcome **before any new data is considered.**
- In simple words, it tells us about what we know based on previous knowledge or experience.
- E:g: - The prior probability could be the distribution of voters who will support a particular candidate in a future election.

Posterior probability

- Posterior probability is a conditional probability that is used to calculate the likelihood of an event occurring **after new information is available.**
- Posterior probability is used to make predictions and decisions based on observed data.
- For example, if you are trying to classify buyers of a specific car, you might know that 60% of buyers are male and 40% are female. You can use this prior probability to calculate the posterior probability of assigning buyers to groups.

Bayes' Rule

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- For example, if a medical test is 90% accurate and yields a positive result, Bayesian reasoning allows for adjusting the probability of having a disease based on this new information

Bayes' Rule

- Mathematically, Bayes theorem is expressed as:

$$P(A \mid B) = (P(B \mid A) * P(A)) / P(B)$$

- **P(A | B)** is the posterior probability, the likelihood of event A happening given that event B has already occurred.
- **P(B | A)** is the likelihood, the probability of observing B if A is true.
- **P(A)** is the prior probability, our initial belief about the chance of event A occurring.
- **P(B)** is the total probability of event B happening (irrespective of A).

Bayes' Rule

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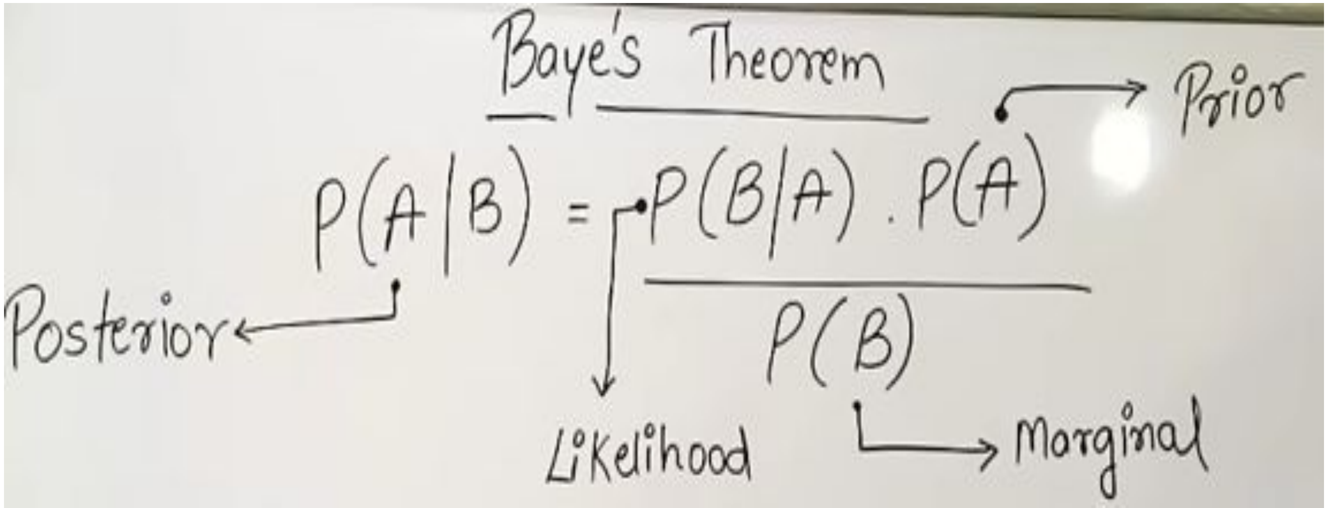


Benefits of Bayes theorem

- **Continuous Learning:** By incorporating new data and evidence, models using Bayes' theorem can constantly improve their performance.
- **Handling Uncertainty:** Bayes' theorem explicitly addresses uncertainty in data, making it suitable for real-world scenarios with incomplete information.
- **Interpretability:** The underlying logic of Bayes' theorem is relatively easy to understand, allowing for better interpretation of model predictions.

Applications of Bayes theorem in AI

1) **Spam Filtering:** spam filters leverage Bayes' theorem to effectively categorize emails.
2) **Image Classification:** Image recognition systems can use Bayes' theorem to assign probabilities to different object categories in an image.
3) **Recommendation Systems:** Recommendation engines can utilize Bayes' theorem to personalize suggestions based on a user's past behavior and preferences.

Applications of Bayes theorem in AI

4) Anomaly Detection: Identifying unusual patterns in data (e.g., fraudulent credit card transactions) often involves Bayes’ theorem to calculate the likelihood of an event being anomalous.

5) Sentiment Analysis: Analyzing the sentiment of text data (positive, negative, or neutral) can be enhanced with Bayes’ theorem by considering the context and prior knowledge about sentiment-related words.

Applications of Bayes theorem in AI

6) Natural Language Processing (NLP): Beyond sentiment analysis, NLP tasks like machine translation and part-of-speech tagging can benefit from Bayes' theorem. It can help determine the most likely translation for a sentence or the most probable part of speech for a word based on surrounding words and context.

7) Medical Diagnosis: While not a replacement for medical expertise, Bayes' theorem can be used in conjunction with patient data and medical history to calculate the probability of a specific disease. This can aid doctors in making informed decisions and prioritizing further tests.

Applications of Bayes theorem in AI

8) Robot Navigation: Robots navigating complex environments can leverage Bayes' theorem to update their understanding of the surroundings based on sensor data. This helps them adapt to changes and avoid obstacles more effectively.

9) Self-Driving Cars: Similar to robot navigation, self-driving cars utilize Bayes' theorem to interpret sensor data (like LiDAR or cameras) and make real-time decisions about steering, braking, and lane changes while considering uncertainties in the environment.

Bayes' Rule

Bayes's Theorem

$$\underbrace{P(A|B)}_{\text{Posterior}} = \frac{\overbrace{P(B|A)}^{\text{Likelihood}} \cdot \overbrace{P(A)}^{\text{Prior}}}{\underbrace{P(B)}_{\text{Marginal}}}$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(B|A) \qquad \frac{P(B \cap A)}{P(B)}$$

$$P(\text{King}|\text{Face}) = \frac{P(\text{Face}|\text{King}) \cdot P(\text{K}}{P(\text{face})} = \frac{1 \cdot 4/52}{12/52}$$

Two bags are there containing Red and black balls; first bag has 3 red and 2 black balls, second bag has 2 red and 3 black balls. One ball is drawn randomly. Find the probability that it is Red ball?

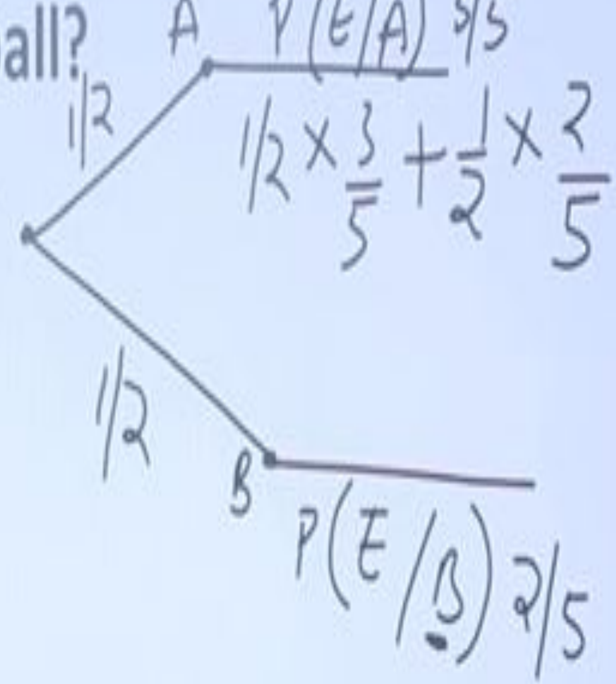
B_1: 3R, 2B

B_2: 2R, 3B

$$P(E) = \text{Red} = P(A)\times P(E/A) + P(B)\times P(E/B)$$

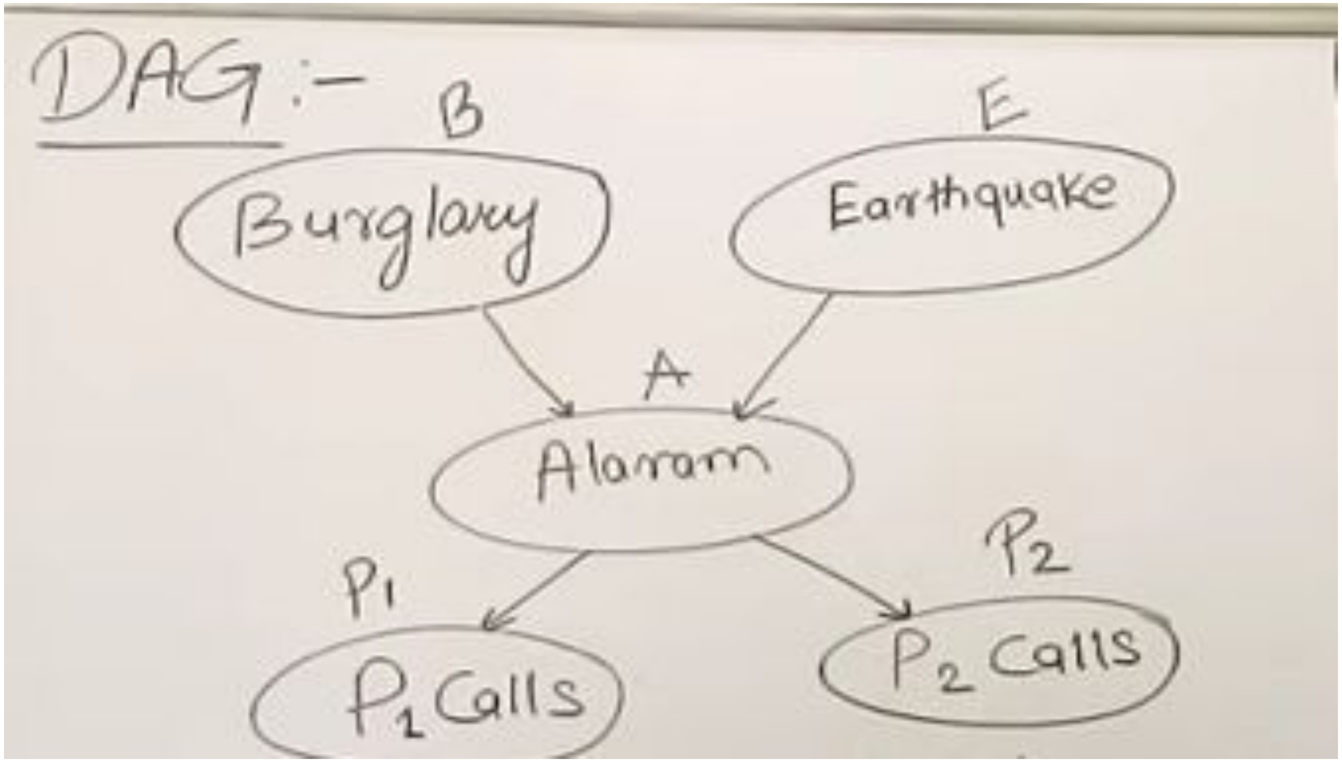
$$P(A) = \text{Bag 1 choose} = 1/2$$

$$P(B) = \text{Bag 2 choose} = 1/2$$



$$\frac{1}{2}\times\frac{3}{5}+\frac{1}{2}\times\frac{2}{5}$$

Bayesian Belief Networks



Bayesian Belief Networks