



JB INSTITUTE OF ENGINEERING & TECHNOLOGY

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**Department of Artificial Intelligence & Machine
Learning**

ARTIFICIAL INTELLIGENCE AND ITS APPLICATIONS

STUDY MATERIAL

UNIT 3

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PREPARED & COMPILED BY

Mrs. Beulah J Karthikeyan Assistant

Professor, Department of AI&ML

JB IET

**Bhaskar Nagar, Yenkapally (V), Moinabad (M), Ranga Reddy,
District Hyderabad., Moinabad,
Hyderabad 500075 Telangana,
India.**

MODULE 3

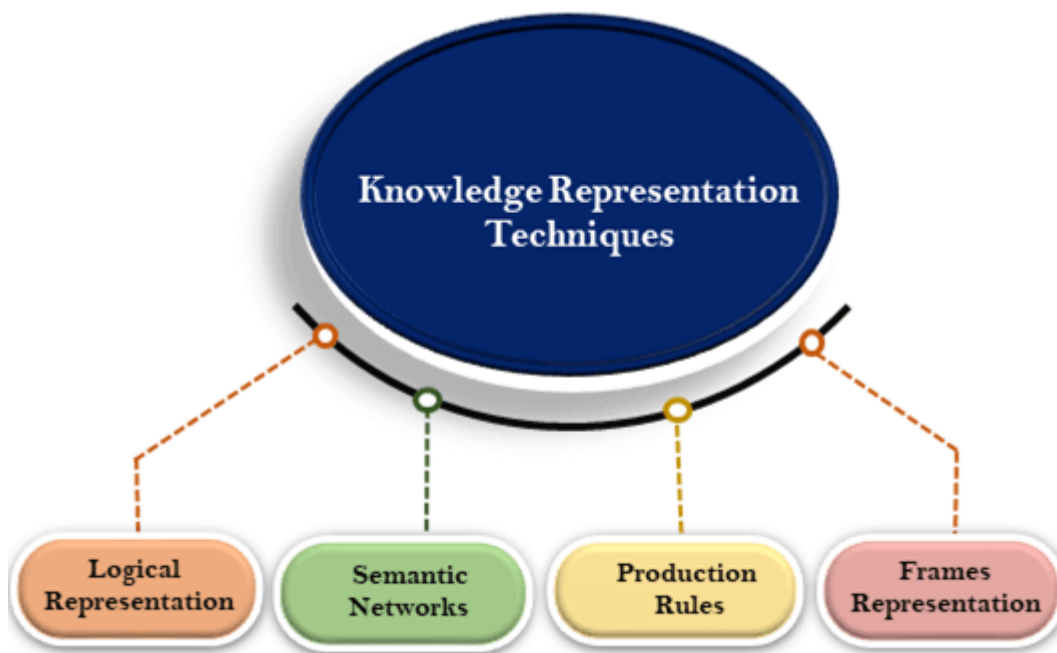
Advanced Knowledge Representation and Reasoning: Knowledge Representation Issues, Nonmonotonic Reasoning, Other Knowledge Representation Schemes.

Reasoning Under Uncertainty: Basic probability, Acting Under Uncertainty, Bayes' Rule, Representing Knowledge in an Uncertain Domain, Bayesian Networks.

Techniques of knowledge representation

There are mainly four ways of knowledge representation which are given as follows:

1. Logical Representation
2. Semantic Network Representation
3. Frame Representation
4. Production Rules



1. Logical Representation

Logical representation is a language with some concrete rules which deals with propositions and has no ambiguity in representation. Logical representation means drawing a conclusion based on various conditions. This representation lays down some important communication rules. It consists of precisely defined syntax and semantics which supports the sound inference. Each sentence can be translated into logics using syntax and semantics.

Syntax:

- Syntaxes are the rules which decide how we can construct legal sentences in the logic.
- It determines which symbol we can use in knowledge representation.
- How to write those symbols.

Semantics:

- Semantics are the rules by which we can interpret the sentence in the logic.
- Semantic also involves assigning a meaning to each sentence.

Logical representation can be categorised into mainly two logics:

- a. Propositional Logics
- b. Predicate logics

Note: We will discuss Propositional Logics and Predicate logics in later chapters.

Advantages of logical representation:

1. Logical representation enables us to do logical reasoning.
2. Logical representation is the basis for the programming languages.

Disadvantages of logical Representation:

1. Logical representations have some restrictions and are challenging to work with.
2. Logical representation technique may not be very natural, and inference may not be so efficient.

Note: Do not be confused with logical representation and logical reasoning as logical representation is a representation language and reasoning is a process of thinking logically.

2. Semantic Network Representation

Semantic networks are alternative of predicate logic for knowledge representation. In Semantic networks, we can represent our knowledge in the form of graphical networks. This network consists of nodes representing objects and arcs which describe the relationship between those objects. Semantic networks can categorize the object in different forms and can also link those objects. Semantic networks are easy to understand and can be easily extended.

This representation consist of mainly two types of relations:

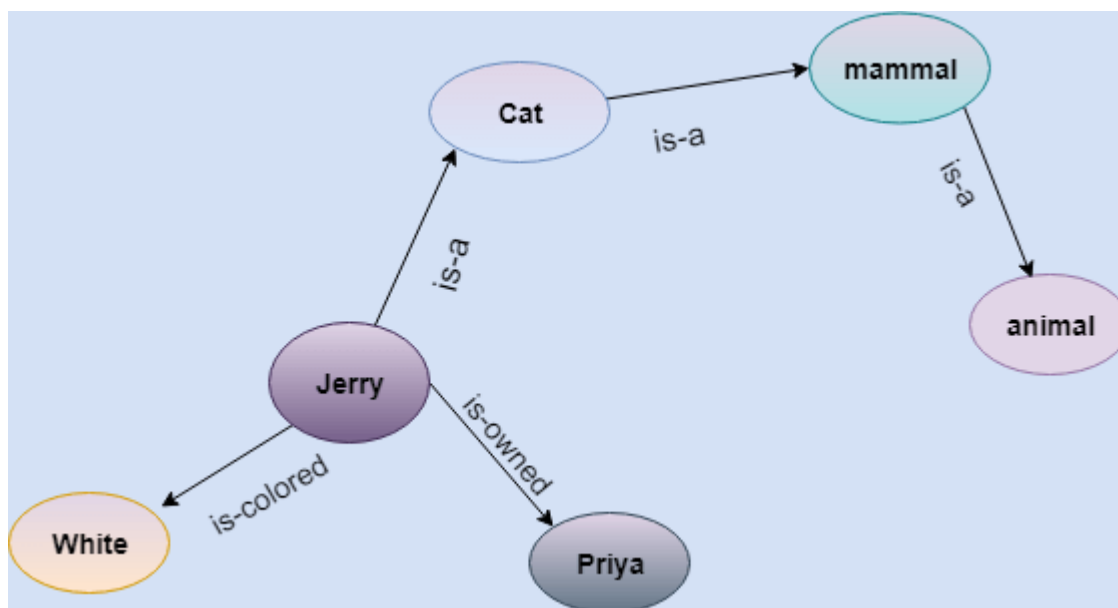
- a. IS-A relation (Inheritance)
- b. Kind-of-relation

Example: Following are some statements which we need to represent in the form of nodes and arcs.

Statements:

- a. Jerry is a cat.
- b. Jerry is a mammal

- c. Jerry is owned by Priya.
- d. Jerry is brown colored.
- e. All Mammals are animal.



In the above diagram, we have represented the different type of knowledge in the form of nodes and arcs. Each object is connected with another object by some relation.

Drawbacks in Semantic representation:

1. Semantic networks take more computational time at runtime as we need to traverse the complete network tree to answer some questions. It might be possible in the worst case scenario that after traversing the entire tree, we find that the solution does not exist in this network.
2. Semantic networks try to model human-like memory (Which has 10¹⁵ neurons and links) to store the information, but in practice, it is not possible to build such a vast semantic network.
3. These types of representations are inadequate as they do not have any equivalent quantifier, e.g., for all, for some, none, etc.
4. Semantic networks do not have any standard definition for the link names.
5. These networks are not intelligent and depend on the creator of the system.

Advantages of Semantic network:

1. Semantic networks are a natural representation of knowledge.
2. Semantic networks convey meaning in a transparent manner.
3. These networks are simple and easily understandable.

3. Frame Representation

A frame is a record like structure which consists of a collection of attributes and its values to describe an entity in the world. Frames are the AI data structure which divides knowledge into substructures by representing stereotypes situations. It consists of a collection of slots and slot values. These slots may be of any type and sizes. Slots have names and values which are called facets.

Facets: The various aspects of a slot is known as **Facets**. Facets are features of frames which enable us to put constraints on the frames. Example: IF-NEEDED facts are called when data of any particular slot is needed. A frame may consist of any number of slots, and a slot may include any number of facets and facets may have any number of values. A frame is also known as **slot-filter knowledge representation** in artificial intelligence.

Frames are derived from semantic networks and later evolved into our modern-day classes and objects. A single frame is not much useful. Frames system consist of a collection of frames which are connected. In the frame, knowledge about an object or event can be stored together in the knowledge base. The frame is a type of technology which is widely used in various applications including Natural language processing and machine visions.

Example: 1

Let's take an example of a frame for a book

Slots	Filters
Title	Artificial Intelligence
Genre	Computer Science
Author	Peter Norvig
Edition	Third Edition
Year	1996
Page	1152

Example 2:

Let's suppose we are taking an entity, Peter. Peter is an engineer as a profession, and his age is 25, he lives in city London, and the country is England. So following is the frame representation for this:

Slots	Filter
Name	Peter
Profession	Doctor
Age	25
Marital status	Single
Weight	78

Advantages of frame representation:

1. The frame knowledge representation makes the programming easier by grouping the related data.
2. The frame representation is comparably flexible and used by many applications in AI.
3. It is very easy to add slots for new attribute and relations.
4. It is easy to include default data and to search for missing values.

5. Frame representation is easy to understand and visualize.

Disadvantages of frame representation:

1. In frame system inference mechanism is not be easily processed.
2. Inference mechanism cannot be smoothly proceeded by frame representation.
3. Frame representation has a much generalized approach.

4. Production Rules

Production rules system consist of (**condition, action**) pairs which mean, "If condition then action". It has mainly three parts:

- The set of production rules
- Working Memory
- The recognize-act-cycle

In production rules agent checks for the condition and if the condition exists then production rule fires and corresponding action is carried out. The condition part of the rule determines which rule may be applied to a problem. And the action part carries out the associated problem-solving steps. This complete process is called a recognize-act cycle.

The working memory contains the description of the current state of problems-solving and rule can write knowledge to the working memory. This knowledge match and may fire other rules.

If there is a new situation (state) generates, then multiple production rules will be fired together, this is called conflict set. In this situation, the agent needs to select a rule from these sets, and it is called a conflict resolution.

Example:

- **IF (at bus stop AND bus arrives) THEN action (get into the bus)**
- **IF (on the bus AND paid AND empty seat) THEN action (sit down).**
- **IF (on bus AND unpaid) THEN action (pay charges).**
- **IF (bus arrives at destination) THEN action (get down from the bus).**

Advantages of Production rule:

1. The production rules are expressed in natural language.
2. The production rules are highly modular, so we can easily remove, add or modify an individual rule.

Disadvantages of Production rule:

1. Production rule system does not exhibit any learning capabilities, as it does not store the result of the problem for the future uses.
2. During the execution of the program, many rules may be active hence rule-based production systems are inefficient.

Issues in Knowledge Representation

The fundamental goal of knowledge Representation is to facilitate inference (conclusions) from knowledge. The issues that arise while using KR techniques are many. Some of these are explained below.

Important Attributes:

Any attribute of objects so basic that they occur in almost every problem domain?

There are two attributed “instance” and “isa”, that are general significance. These attributes are important because they support property inheritance.

Relationship among attributes:

Any important relationship that exists among object attributed?

The attributes we use to describe objects are themselves entities that we represent.

The relationship between the attributes of an object, independent of specific knowledge they encode, may hold properties like:

1. Inverse — This is about consistency check, while a value is added to one attribute. The entities are related to each other in many different ways.
2. Existence in an isa hierarchy — This is about generalization-specification, like, classes of objects and specialized subsets of those classes, there are attributes and specialization of attributes. For example, the attribute height is a specialization of general attribute physical-size which is, in turn, a specialization of physical-attribute. These generalization-specialization relationships are important for attributes because they support inheritance.
3. Technique for reasoning about values — This is about reasoning values of attributes not given explicitly. Several kinds of information are used in reasoning, like, height: must be in a unit of length, Age: of a person cannot be greater than the age of person's parents. The values are often specified when a knowledge base is created.
4. Single valued attributes — This is about a specific attribute that is guaranteed to take a unique value. For example, a baseball player can at time have only a single height and be a member of only one team. KR systems take different approaches to provide support for single valued attributes.

Choosing Granularity:

At what level of detail should the knowledge be represented?

Regardless of the KR formalism, it is necessary to know:

At what level should the knowledge be represented and what are the primitives?

- Should there be a small number or should there be a large number of low-level primitives or High-level facts.

- High-level facts may not be adequate for inference while Low-level primitives may require a lot of storage.
- Example of Granularity:
- Suppose we are interested in following facts:

John spotted Sue.

This could be represented as

Spotted (agent(John),object (Sue))

Such a representation would make it easy to answer questions such are:

- Who spotted Sue?

Suppose we want to know:

- Did John see Sue?

Given only one fact, we cannot discover that answer.

We can add other facts, such as

Spotted(x, y) -> saw(x, y)

We can now infer the answer to the question.

Set of objects:

How should sets of objects be represented?

There are certain properties of objects that are true as member of a set but not as individual;

Example: Consider the assertion made in the sentences:

“there are more sheep than people in Australia”, and

“English speakers can be found all over the world.”

To describe these facts, the only way is to attach assertion to the sets representing people, sheep, and English.

The reason to represent sets of objects is: if a property is true for all or most elements of a set, then it is more efficient to associate it once with the set rather than to associate it explicitly with every elements of the set.

This is done,

in logical representation through the use of universal quantifier, and

- in hierarchical structure where node represent sets and inheritance propagate set level assertion down to individual.

Finding Right structure:

Given a large amount of knowledge stored in a database, how can relevant parts are accessed when they are needed?

This is about access to right structure for describing a particular situation.

This requires, selecting an initial structure and then revising the choice.

While doing so, it is necessary to solve following problems:

- How to perform an initial selection of the most appropriate structure.
- How to fill in appropriate details from the current situations.
- How to find a better structure if the one chosen initially turns out not to be appropriate.
- What to do if none of the available structures is appropriate.
- When to create and remember a new structure.

There is no good, general purpose method for solving all these problems. Some knowledge representation techniques solve some of these issues.

Monotonic Reasoning:

In monotonic reasoning, once the conclusion is taken, then it will remain the same even if we add some other information to existing information in our knowledge base. In monotonic reasoning, adding knowledge does not decrease the set of prepositions that can be derived.

To solve monotonic problems, we can derive the valid conclusion from the available facts only, and it will not be affected by new facts.

Monotonic reasoning is not useful for the real-time systems, as in real time, facts get changed, so we cannot use monotonic reasoning.

Monotonic reasoning is used in conventional reasoning systems, and a logic-based system is monotonic.

Any theorem proving is an example of monotonic reasoning.

Example:

- **Earth revolves around the Sun.**

It is a true fact, and it cannot be changed even if we add another sentence in knowledge base like, "The moon revolves around the earth" Or "Earth is not round," etc.

Advantages of Monotonic Reasoning:

- In monotonic reasoning, each old proof will always remain valid.
- If we deduce some facts from available facts, then it will remain valid for always.

Disadvantages of Monotonic Reasoning:

- We cannot represent the real world scenarios using Monotonic reasoning.
- Hypothesis knowledge cannot be expressed with monotonic reasoning, which means facts should be true.
- Since we can only derive conclusions from the old proofs, so new knowledge from the real world cannot be added.

Non-monotonic Reasoning

In Non-monotonic reasoning, some conclusions may be invalidated if we add some more information to our knowledge base.

Logic will be said as non-monotonic if some conclusions can be invalidated by adding more knowledge into our knowledge base.

Non-monotonic reasoning deals with incomplete and uncertain models.

"Human perceptions for various things in daily life, "is a general example of non-monotonic reasoning.

Example: Let suppose the knowledge base contains the following knowledge:

- **Birds can fly**
- **Penguins cannot fly**
- **Pitty is a bird**

So from the above sentences, we can conclude that **Pitty can fly**.

However, if we add one another sentence into knowledge base "**Pitty is a penguin**", which concludes "**Pitty cannot fly**", so it invalidates the above conclusion.

Advantages of Non-monotonic reasoning:

- For real-world systems such as Robot navigation, we can use non-monotonic reasoning.
- In Non-monotonic reasoning, we can choose probabilistic facts or can make assumptions.

Disadvantages of Non-monotonic Reasoning:

- In non-monotonic reasoning, the old facts may be invalidated by adding new sentences.
- It cannot be used for theorem **proving**.

Probabilistic reasoning in Artificial intelligence Uncertainty:

Till now, we have learned knowledge representation using first-order logic and propositional logic with certainty, which means we were sure about the predicates. With this knowledge representation, we might write $A \rightarrow B$, which means if A is true then B is true, but consider a situation where we are not sure about whether A is true or not then we cannot express this statement, this situation is called uncertainty.

So to represent uncertain knowledge, where we are not sure about the predicates, we need uncertain reasoning or probabilistic reasoning.

Causes of uncertainty:

Following are some leading causes of uncertainty to occur in the real world.

1. Information occurred from unreliable sources.
2. Experimental Errors
3. Equipment fault
4. Temperature variation
5. Climate change.

Probabilistic reasoning:

Probabilistic reasoning is a way of knowledge representation where we apply the concept of probability to indicate the uncertainty in knowledge. In probabilistic reasoning, we combine probability theory with logic to handle the uncertainty.

We use probability in probabilistic reasoning because it provides a way to handle the uncertainty that is the result of someone's laziness and ignorance.

In the real world, there are lots of scenarios, where the certainty of something is not confirmed, such as "It will rain today," "behavior of someone for some situations," "A match between two teams or two players." These are probable sentences for which we can assume that it will happen but not sure about it, so here we use probabilistic reasoning.

Need of probabilistic reasoning in AI:

- When there are unpredictable outcomes.
- When specifications or possibilities of predicates becomes too large to handle.

- When an unknown error occurs during an experiment.

In probabilistic reasoning, there are two ways to solve problems with uncertain knowledge:

- **Bayes' rule**
- **Bayesian Statistics**

Note: We will learn the above two rules in later chapters.

As probabilistic reasoning uses probability and related terms, so before understanding probabilistic reasoning, let's understand some common terms:

Probability: Probability can be defined as a chance that an uncertain event will occur. It is the numerical measure of the likelihood that an event will occur. The value of probability always remains between 0 and 1 that represent ideal uncertainties.

1. $0 \leq P(A) \leq 1$, where $P(A)$ is the probability of an event A .
1. $P(A) = 0$, indicates total uncertainty in an event A .
1. $P(A) = 1$, indicates total certainty in an event A .

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

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

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

Event: Each possible outcome of a variable is called an event.

Sample space: The collection of all possible events is called sample space.

Random variables: Random variables are used to represent the events and objects in the real world.

Prior probability: The prior probability of an event is probability computed before observing new information.

Posterior Probability: The probability that is calculated after all evidence or information has taken into account. It is a combination of prior probability and new information.

Conditional probability:

Conditional probability is a probability of occurring an event when another event has already happened.

Let's suppose, we want to calculate the event A when event B has already occurred, "the probability of A under the conditions of B ", it can be written as:

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

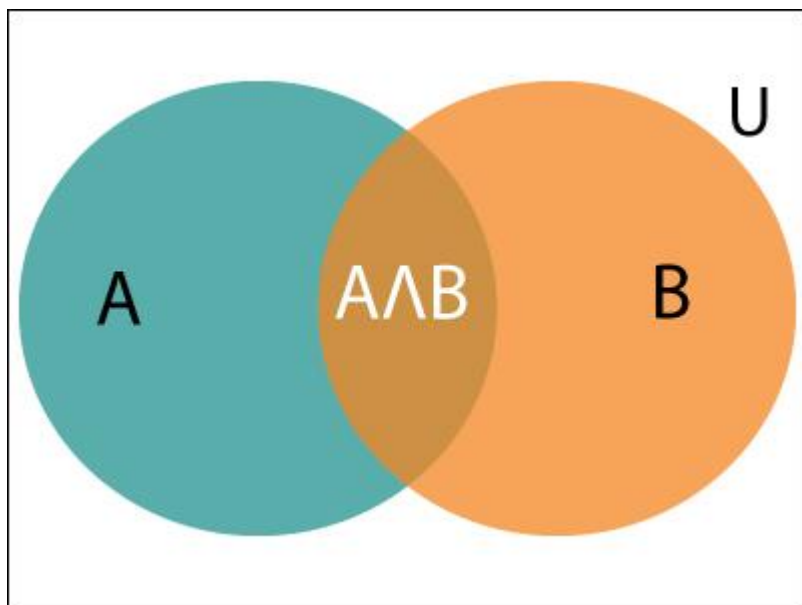
Where $P(A \cap B)$ = Joint probability of A and B

P(B)= Marginal probability of B.

If the probability of A is given and we need to find the probability of B, then it will be given as:

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

It can be explained by using the below Venn diagram, where B is occurred event, so sample space will be reduced to set B, and now we can only calculate event A when event B is already occurred by dividing the probability of **P(A∩B)** by **P(B)**.



Example:

In a class, there are 70% of the students who like English and 40% of the students who likes English and mathematics, and then what is the percent of students those who like English also like mathematics?

Solution:

Let, A is an event that a student likes Mathematics

B is an event that a student likes English.

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{0.4}{0.7} = 57\%$$

Hence, 57% are the students who like English also like Mathematics.

Acting Under Uncertainty

To act rationally under uncertainty we must be able to evaluate how likely certain things are. With FOL a fact F is only useful if it is known to be true or false. But we need to be able to evaluate how likely it is that F is true. By weighing likelihoods of events (probabilities) we can develop mechanisms for acting rationally under uncertainty.

Dental Diagnosis example.

In FOL we might formulate

$P. \text{symptom}(P, \text{toothache}) \rightarrow \text{disease}(p, \text{cavity}) \quad \text{disease}(p, \text{gumDisease})$
 $\text{disease}(p, \text{foodStuck})$

When do we stop?

Cannot list all possible causes.

We also want to rank the possibilities. We don't want to start drilling for a cavity before checking for more likely causes first.

Axioms Of Probability

Given a set U (universe), a probability function is a function defined over the subsets of U that maps each subset to the real numbers and that satisfies the Axioms of Probability

$$1. \Pr(U) = 1$$

$$2. \Pr(A) \in [0, 1]$$

$$3. \Pr(A \cup B) = \Pr(A) + \Pr(B) - \Pr(A \cap B)$$

U

Note if $A \cap B = \{\}$ then $\Pr(A \cup B) = \Pr(A) + \Pr(B)$

2. REVIEW OF PROBABILITY

- Natural way to represent uncertainty
- People have intuitive notions about probabilities
- Many of these are wrong or inconsistent
- Most people don't get what probabilities mean
- Understanding Probabilities
- Initially, probabilities are "relative frequencies"
- This works well for dice and coin flips
- For more complicated events, this is problematic

- What is the probability that Obama will be reelected?
- This event only happens once
- We can't count frequencies
- still seems like a meaningful question
- In general, all events are unique
- **Probabilities and Beliefs**
- Suppose I have flipped a coin and hidden the outcome
- What is $P(\text{Heads})$?
- Note that this is a statement about a belief, not a statement about the world
- The world is in exactly one state (at the macro level) and it is in that state with probability 1.
- Assigning truth values to probability statements is very tricky business
- Must reference speakers state of knowledge
- **Frequentism and Subjectivism**
- Frequentists hold that probabilities must come from relative frequencies
- This is a purist viewpoint
- This is corrupted by the fact that relative frequencies are often unobtainable
- Often requires complicated and convoluted
- assumptions to come up with probabilities
- Subjectivists: probabilities are degrees of belief
- Taints purity of probabilities
- Often more practical

Bayes' theorem in Artificial intelligence

Bayes' theorem:

Bayes' theorem is also known as **Bayes' rule**, **Bayes' law**, or **Bayesian reasoning**, which determines the probability of an event with uncertain knowledge.

In probability theory, it relates the conditional probability and marginal probabilities of two random events.

Bayes' theorem was named after the British mathematician **Thomas Bayes**. The **Bayesian inference** is an application of Bayes' theorem, which is fundamental to Bayesian statistics.

It is a way to calculate the value of $P(B|A)$ with the knowledge of $P(A|B)$.

Bayes' theorem allows updating the probability prediction of an event by observing new information of the real world.

Example: If cancer corresponds to one's age then by using Bayes' theorem, we can determine the probability of cancer more accurately with the help of age.

Bayes' theorem can be derived using product rule and conditional probability of event A with known event B:

As from product rule we can write:

1. $P(A \wedge B) = P(A|B) P(B)$ or

Similarly, the probability of event B with known event A:

1. $P(A \wedge B) = P(B|A) P(A)$

Equating right hand side of both the equations, we will get:

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)} \quad \dots(a)$$

The above equation (a) is called as **Bayes' rule** or **Bayes' theorem**. This equation is basic of most modern AI systems for **probabilistic inference**.

It shows the simple relationship between joint and conditional probabilities. Here,

$P(A|B)$ is known as **posterior**, which we need to calculate, and it will be read as Probability of hypothesis A when we have occurred an evidence B.

$P(B|A)$ is called the **likelihood**, in which we consider that hypothesis is true, then we calculate the probability of evidence.

$P(A)$ is called the **prior probability**, probability of hypothesis before considering the evidence

$P(B)$ is called **marginal probability**, pure probability of an evidence.

In the equation (a), in general, we can write $P(B) = \sum_{i=1}^k P(A_i) * P(B|A_i)$, hence the Bayes' rule can be written as:

$$P(A_i|B) = \frac{P(A_i) * P(B|A_i)}{\sum_{i=1}^k P(A_i) * P(B|A_i)}$$

Where $A_1, A_2, A_3, \dots, A_n$ is a set of mutually exclusive and exhaustive events.

Applying Bayes' rule:

Bayes' rule allows us to compute the single term $P(B|A)$ in terms of $P(A|B)$, $P(B)$, and $P(A)$. This is very useful in cases where we have a good probability of these three terms and want to determine the fourth one. Suppose we want to perceive the effect of some unknown cause, and want to compute that cause, then the Bayes' rule becomes:

$$P(\text{cause} | \text{effect}) = \frac{P(\text{effect} | \text{cause}) P(\text{cause})}{P(\text{effect})}$$

Example-1:

Question: what is the probability that a patient has diseases meningitis with a stiff neck?

Given Data:

A doctor is aware that disease meningitis causes a patient to have a stiff neck, and it occurs 80% of the time. He is also aware of some more facts, which are given as follows:

- The Known probability that a patient has meningitis disease is 1/30,000.
- The Known probability that a patient has a stiff neck is 2%.

Let a be the proposition that patient has stiff neck and b be the proposition that patient has meningitis. , so we can calculate the following as:

$$P(a|b) = 0.8$$

$$P(b) = 1/30000$$

$$P(a) = .02$$

$$P(b|a) = \frac{P(a|b)P(b)}{P(a)} = \frac{0.8 * (\frac{1}{30000})}{0.02} = 0.001333333.$$

Hence, we can assume that 1 patient out of 750 patients has meningitis disease with a stiff neck.

Example-2:

Question: From a standard deck of playing cards, a single card is drawn. The probability that the card is king is 4/52, then calculate posterior probability P(King|Face), which means the drawn face card is a king card.

Solution:

$$P(\text{king} | \text{face}) = \frac{P(\text{Face} | \text{king}) * P(\text{King})}{P(\text{Face})} \dots\dots(i)$$

P(king): probability that the card is King= 4/52= 1/13

P(face): probability that a card is a face card= 3/13

P(Face|King): probability of face card when we assume it is a king = 1

Putting all values in equation (i) we will get:

$$P(\text{king}|\text{face}) = \frac{1 * (\frac{1}{13})}{(\frac{3}{13})} = 1/3, \text{ it is a probability that a face card is a king card.}$$

Application of Bayes' theorem in Artificial intelligence:

Following are some applications of Bayes' theorem:

- It is used to calculate the next step of the robot when the already executed step is given.
- Bayes' theorem is helpful in weather forecasting.
- It can solve the Monty Hall problem.

Bayesian Belief Network in artificial intelligence

Bayesian belief network is key computer technology for dealing with probabilistic events and to solve a problem which has uncertainty. We can define a Bayesian network as:

"A Bayesian network is a probabilistic graphical model which represents a set of variables and their conditional dependencies using a directed acyclic graph."

It is also called a **Bayes network**, **belief network**, **decision network**, or **Bayesian model**.

Bayesian networks are probabilistic, because these networks are built from a **probability distribution**, and also use probability theory for prediction and anomaly detection.

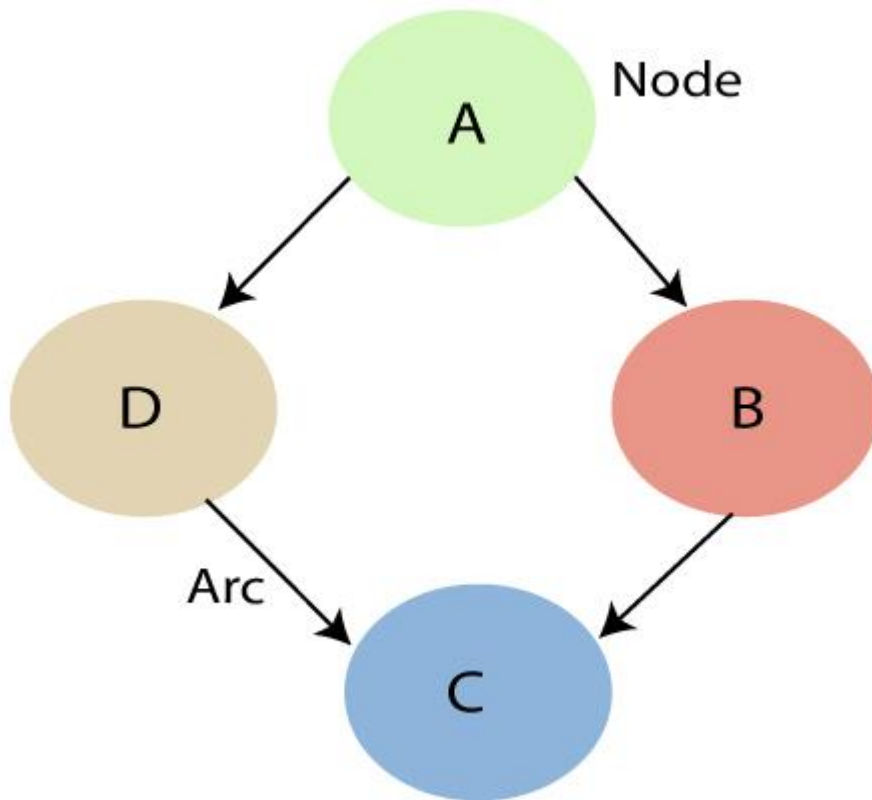
Real world applications are probabilistic in nature, and to represent the relationship between multiple events, we need a Bayesian network. It can also be used in various tasks including **prediction**, **anomaly detection**, **diagnostics**, **automated insight**, **reasoning**, **time series prediction**, and **decision making under uncertainty**.

Bayesian Network can be used for building models from data and experts opinions, and it consists of two parts:

- **Directed Acyclic Graph**
- **Table of conditional probabilities.**

The generalized form of Bayesian network that represents and solve decision problems under uncertain knowledge is known as an **Influence diagram**.

A **Bayesian network graph** is made up of **nodes** and **Arcs (directed links)**, where:



- Each **node** corresponds to the random variables, and a variable can be **continuous** or **discrete**.
- **Arc or directed arrows** represent the causal relationship or conditional probabilities between random variables. These directed links or arrows connect the pair of nodes in the graph. These links represent that one node directly influence the other node, and if there is no directed link that means that nodes are independent with each other
 - In the above diagram, A, B, C, and D are random variables represented by the nodes of the network graph.
 - If we are considering node B, which is connected with node A by a directed arrow, then node A is called the parent of Node B.
 - Node C is independent of node A.

Note: The Bayesian network graph does not contain any cyclic graph. Hence, it is known as a directed acyclic graph or DAG.

The Bayesian network has mainly two components:

- **Causal Component**
- **Actual numbers**

Each node in the Bayesian network has condition probability distribution $P(X_i | \text{Parent}(X_i))$, which determines the effect of the parent on that node.

Bayesian network is based on Joint probability distribution and conditional probability. So let's first understand the joint probability distribution:

Joint probability distribution:

If we have variables $x_1, x_2, x_3, \dots, x_n$, then the probabilities of a different combination of $x_1, x_2, x_3 \dots x_n$, are known as Joint probability distribution.

$P[x_1, x_2, x_3, \dots, x_n]$, it can be written as the following way in terms of the joint probability distribution.

$$= P[x_1 | x_2, x_3, \dots, x_n] P[x_2, x_3, \dots, x_n]$$

$$= P[x_1 | x_2, x_3, \dots, x_n] P[x_2 | x_3, \dots, x_n] \dots P[x_{n-1} | x_n] P[x_n].$$

In general for each variable X_i , we can write the equation as:

$$P(X_i | X_{i-1}, \dots, X_1) = P(X_i | \text{Parents}(X_i))$$

Explanation of Bayesian network:

Let's understand the Bayesian network through an example by creating a directed acyclic graph:

Example: Harry installed a new burglar alarm at his home to detect burglary. The alarm reliably responds at detecting a burglary but also responds for minor earthquakes. Harry has two neighbors David and Sophia, who have taken a responsibility to inform Harry at work when they hear the alarm. David always calls Harry when he hears the alarm, but sometimes he got confused with the phone ringing and calls at that time too. On the other hand, Sophia likes to listen to high music, so sometimes she misses to hear the alarm. Here we would like to compute the probability of Burglary Alarm.

Problem:

Calculate the probability that alarm has sounded, but there is neither a burglary, nor an earthquake occurred, and David and Sophia both called the Harry.

Solution:

- The Bayesian network for the above problem is given below. The network structure is showing that burglary and earthquake is the parent node of the alarm and directly affecting the probability of alarm's going off, but David and Sophia's calls depend on alarm probability.
- The network is representing that our assumptions do not directly perceive the burglary and also do not notice the minor earthquake, and they also not confer before calling.
- The conditional distributions for each node are given as conditional probabilities table or CPT.
- Each row in the CPT must be sum to 1 because all the entries in the table represent an exhaustive set of cases for the variable.
- In CPT, a boolean variable with k boolean parents contains 2^k probabilities. Hence, if there are two parents, then CPT will contain 4 probability values

List of all events occurring in this network:

- **Burglary (B)**
- **Earthquake(E)**
- **Alarm(A)**

- David Calls(D)
- Sophia calls(S)

We can write the events of problem statement in the form of probability: $P[D, S, A, B, E]$, can rewrite the above probability statement using joint probability distribution:

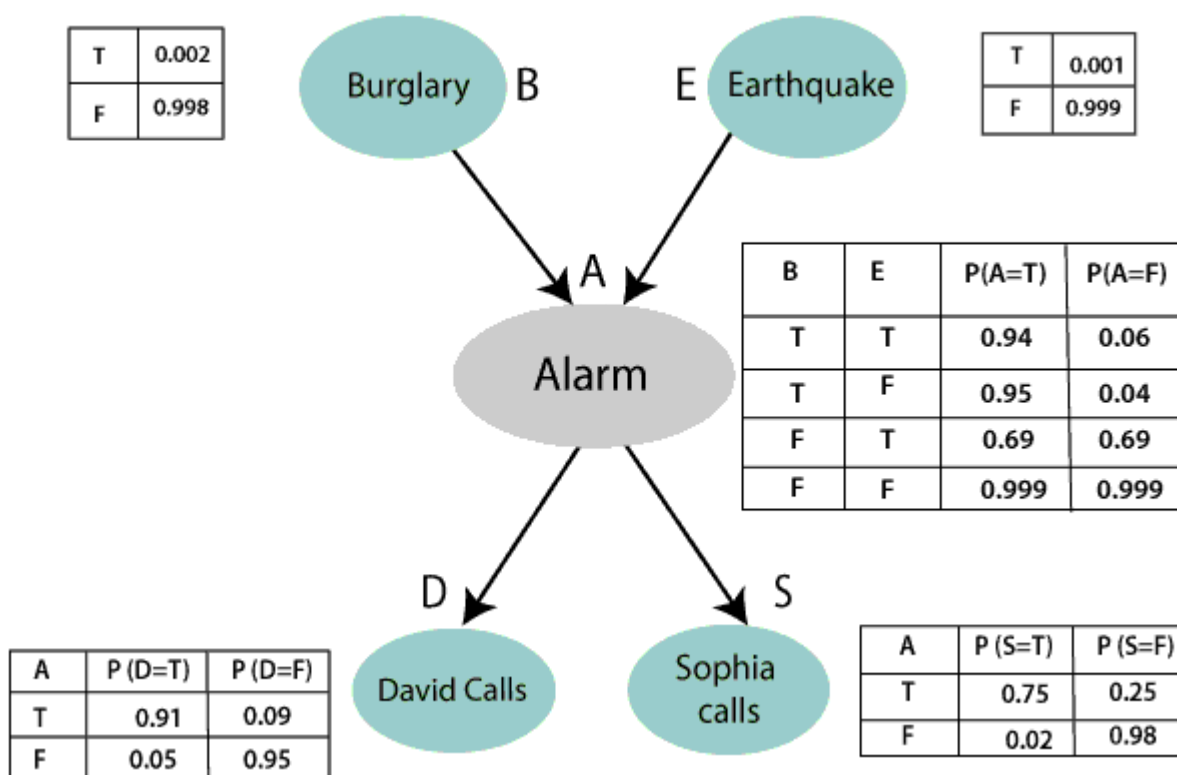
$$P[D, S, A, B, E] = P[D | S, A, B, E] \cdot P[S, A, B, E]$$

$$= P[D | S, A, B, E] \cdot P[S | A, B, E] \cdot P[A, B, E]$$

$$= P[D | A] \cdot P[S | A, B, E] \cdot P[A, B, E]$$

$$= P[D | A] \cdot P[S | A] \cdot P[A | B, E] \cdot P[B, E]$$

$$= P[D | A] \cdot P[S | A] \cdot P[A | B, E] \cdot P[B | E] \cdot P[E]$$



Let's take the observed probability for the Burglary and earthquake component:

$P(B = \text{True}) = 0.002$, which is the probability of burglary.

$P(B = \text{False}) = 0.998$, which is the probability of no burglary.

$P(E = \text{True}) = 0.001$, which is the probability of a minor earthquake

$P(E = \text{False}) = 0.999$, Which is the probability that an earthquake not occurred.

We can provide the conditional probabilities as per the below tables:

Conditional probability table for Alarm A:

The Conditional probability of Alarm A depends on Burglar and earthquake:

B	E	P(A= True)	P(A= False)
True	True	0.94	0.06
True	False	0.95	0.04
False	True	0.31	0.69
False	False	0.001	0.999

Conditional probability table for David Calls:

The Conditional probability of David that he will call depends on the probability of Alarm.

A	P(D= True)	P(D= False)
True	0.91	0.09
False	0.05	0.95

Conditional probability table for Sophia Calls:

The Conditional probability of Sophia that she calls is depending on its Parent Node "Alarm."

A	P(S= True)	P(S= False)
True	0.75	0.25
False	0.02	0.98

From the formula of joint distribution, we can write the problem statement in the form of probability distribution:

$$P(S, D, A, \neg B, \neg E) = P(S|A) * P(D|A) * P(A|\neg B \wedge \neg E) * P(\neg B) * P(\neg E).$$

$$= 0.75 * 0.91 * 0.001 * 0.998 * 0.999$$

$$= \mathbf{0.00068045}.$$

Hence, a Bayesian network can answer any query about the domain by using Joint distribution.

The semantics of Bayesian Network:

There are two ways to understand the semantics of the Bayesian network, which is given below:

1. To understand the network as the representation of the Joint probability distribution.

It is helpful to understand how to construct the network.

2. To understand the network as an encoding of a collection of conditional independence statements.

It is helpful in designing inference procedure.

