4.19 BELIEF NETWORKS

- A Bayesian network, Bayes network, belief network, Bayes(ian) model or probabilistic directed acyclic graphical model is a probabilistic graphical model (a type of statistical model) that represents a set of random variables and their conditional dependencies via a **directed acyclic graph (DAG).** 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.
- **There are two components that define a Bayesian Belief Network** :

  (i) Directed acyclic graph

  (ii) A set of conditional probability tables

(i) Directed Acyclic Graph:

- Each node in a directed acyclic graph represents a random variable.
- These variable may be discrete or continuous valued.
- These variables may correspond to the actual attribute given in the data.

Fig. 4.31 shows a directed acyclic graph for six Boolean variables.

The arc in the diagram allows representation of causal knowledge.

For example, lung cancer is influenced by a person's family history of lung cancer, as well as whether or not the person is a smoker. It is worth noting that the variable Positive X-ray is independent of whether the patient has a family history of lung cancer or that the patient is a smoker, given that we know the patient has lung cancer.

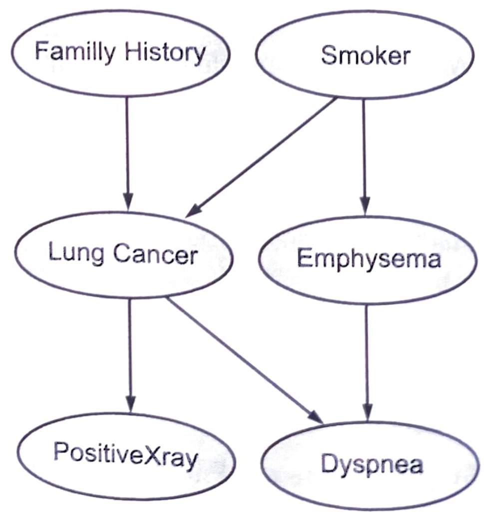


Fig. 4.31: Directed Acyclic Graph

As a part of the domain, assume the following conditional independencies:

- Fire is conditionally independent of Tampering (given no other information).
- Alarm depends on both Fire and Tampering. That is, we are making no independence assumptions about how Alarm depends on its predecessors given this variable ordering.
- Smoke depends only on Fire and is conditionally independent of Tampering and Alarm given whether there is a Fire.
- Leaving only depends on Alarm and not directly on Fire or Tampering or Smoke. That is, Leaving is conditionally independent of the other variables given Alarm.
- Report only directly depends on Leaving.

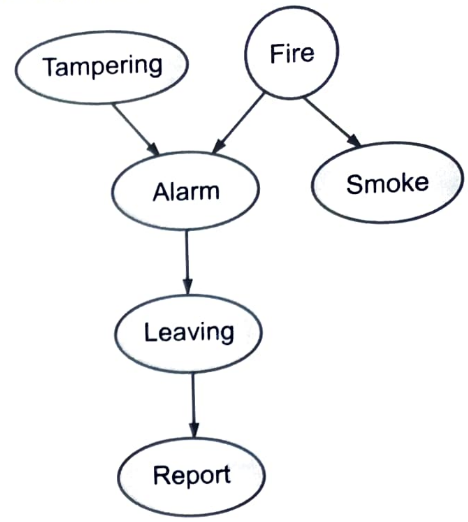


Fig. 4.32 (a): Belief Network Figure Showing Dependencies

The belief network shown in Fig. 4.32 (a) expresses these dependencies :

(ii) Conditional Probability Table:

The conditional probability table for the values of the variable Lung Cancer (LC) showing each possible combination of the values of its parent nodes, Family History (FH), and Smoker (S) is shown in Fig. 4.32 (b).

	FH,S	FH,–S	–FH,S	–FH,S
LC	0.8	0.5	0.7	0.1
–LC	0.2	0.5	0.3	0.9

Fig. 4.32 (b): Conditional Probability Table

Example 4.18: *Assume your house has an alarm system against burglary. You live in the seismically active area and the alarm system can get occasionally set off by an earthquake. You have two neighbours, Mary and John, who do not know each other. If they hear the alarm they call you, but this is not guaranteed.*

We want to represent the probability distribution of events: – Burglary, Earthquake, Alarm, Mary calls and John calls. **(MU - Q.2 (a), May 17, 10 Marks, Q.4 (a), Dec. 16, 10 Marks)**

Solution :

Causal relations

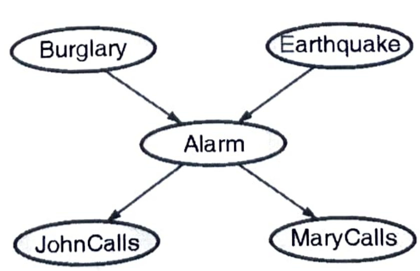


Fig. 4.33: Probability Distribution of Events

(i) Directed acyclic graph:

- Nodes = random variables Burglary, Earthquake, Alarm, Mary calls and John calls.
- Links = direct (causal) dependencies between variables. The chance of Alarm is influenced by Earthquake, The chance of John calling is affected by the Alarm.

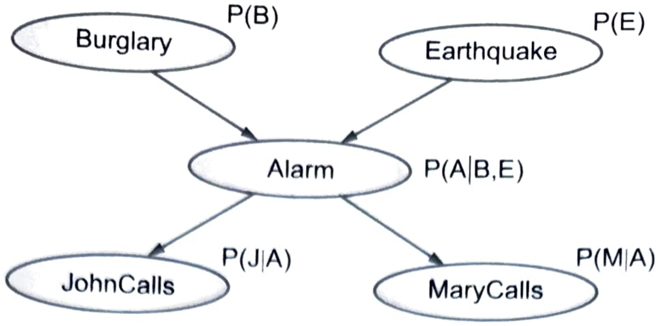


Fig. 4.33 (a): Directed Acyclic Graph

(ii) Local conditional distributions

- Relate variables and their parents

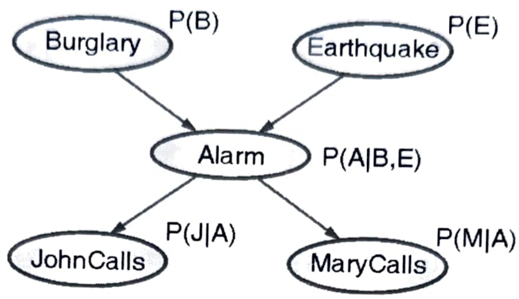
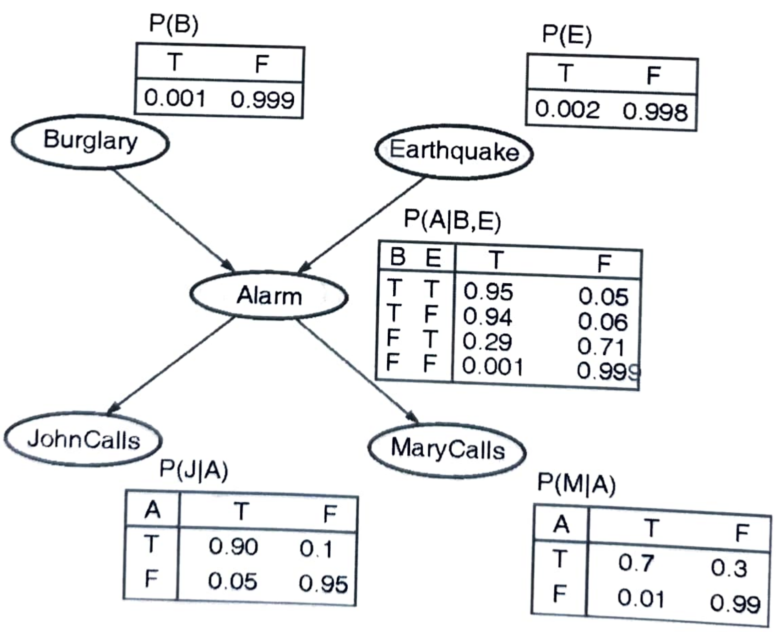


Fig. 4.33 (b): Local Conditional Distributions

(iii) In the Bayesian Belief Network (BBN) shown in Fig. 4.33 (c) the full joint distribution is expressed using a set of logical conditional distributions:



P(B)

T	F
0.001	0.999

P(E)

T	F
0.002	0.998

P(A|B,E)

B	E	T	F
T	T	0.95	0.05
T	F	0.94	0.06
F	T	0.29	0.71
F	F	0.001	0.999

P(J|A)

A	T	F
T	0.90	0.1
F	0.05	0.95

P(M|A)

A	T	F
T	0.7	0.3
F	0.01	0.99

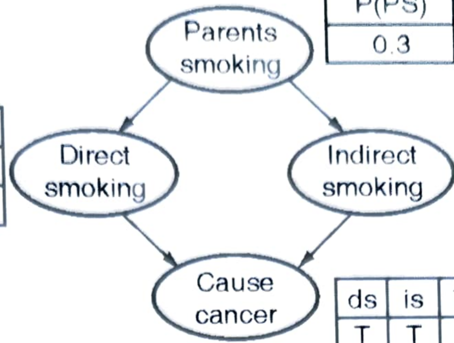
Fig. 4.33 (c) : Probability distributions

Example 4.19: *It is known that whether or not a person has cancer is directly influenced by whether she is exposed to second-hand smoke and whether she smokes. Both of these things are affected by whether her parents smoke. Cancer reduces a person's life expectancy.*

(i) *Draw the Bayesian belief network for the above situation.*

(ii) *Associate a conditional probability table for each node.*

Solution :



P(PS)
0.3

ps	P(DS/PS = ps)
T	0.75
F	0.25

ps	P(IS/PS = ps)
T	0.55
F	0.02

ds	is	1(c/DS = ds, IS = is)
T	T	0.41
T	F	0.33
F	T	0.13
F	F	0.11

Fig. 4.34

Hence, a Bayesian network Fig. 4.34 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.