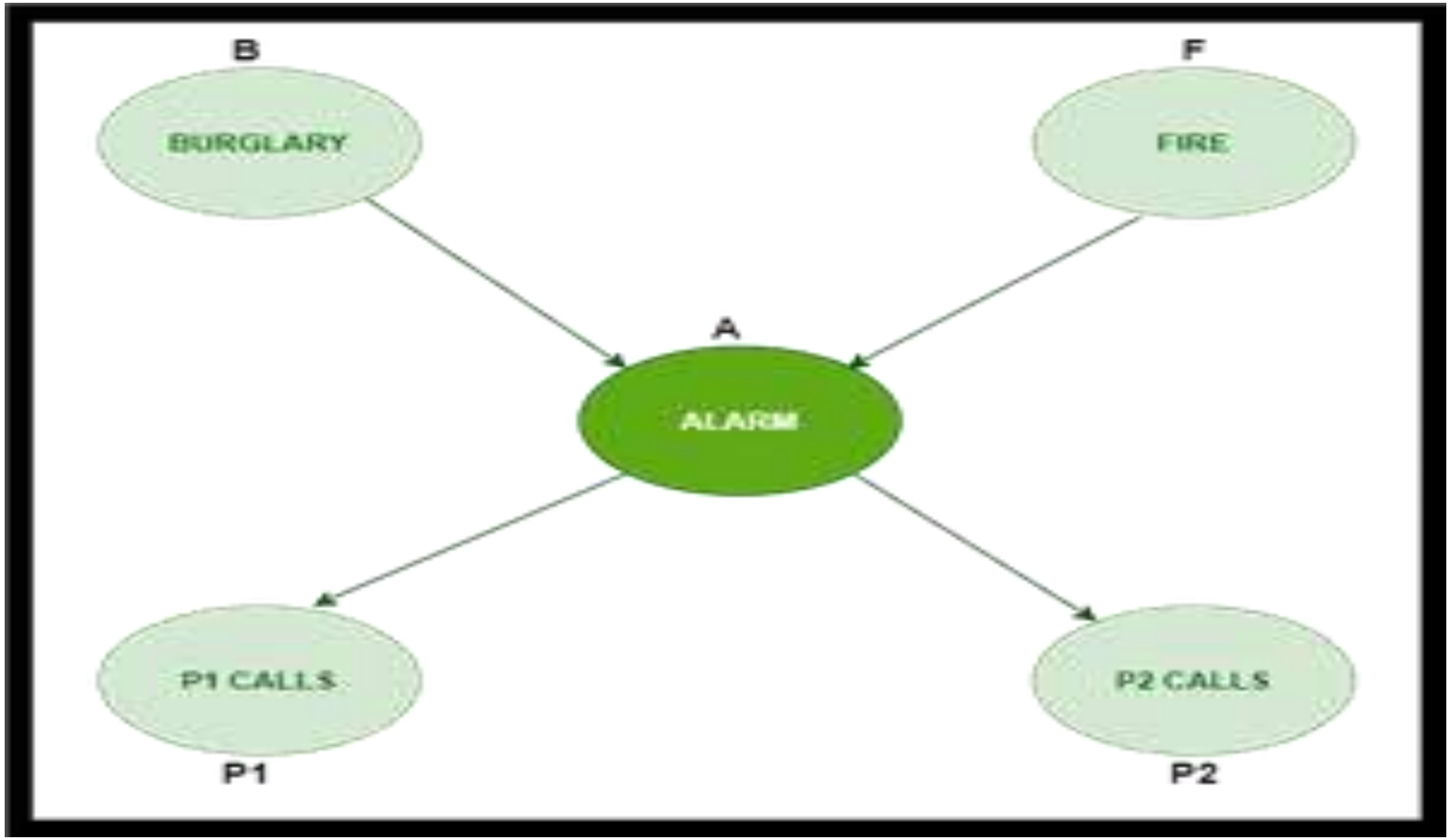
Bayesian networks

Bayesian networks

- Bayesian networks are a widely-used class of probabilistic graphical models.
- They consist of two parts: a structure and parameters.
- The structure is a directed acyclic graph (DAG)
- Refers to a directed graph which has no directed cycles.
- Each edge is associated with a direction from a start vertex to an end vertex.
- If we traverse along the direction of the edges and we find that no closed loops are formed along any path.

- Structure expresses conditional independencies and dependencies among random variables associated with nodes.
- The parameters consist of conditional probability distributions associated with each node.
- Bayesian network is a graphical representation of different probabilistic relationships among random variables in a particular set.
- It is a classifier with no dependency on attributes i.e it is condition independent.
- Due to its feature of joint probability, the probability in Bayesian Belief Network is derived, based on a condition —
- P(attribute/parent) i.e probability of an attribute, true over parent attribute.

Example:



- we have an alarm ‘A’ – a node, say installed in a house which rings upon two probabilities
- i.e burglary ‘B’ and fire ‘F’, which are – parent nodes of the alarm node.
- The alarm is the parent node of two probabilities P1 calls or

  P2 calls person.
- ‘P1’ and ‘P2’ call person ‘gfg’, respectively.
- But, there are few drawbacks in this case, as sometimes ‘P1’ may forget to call person.
- Similarly, ‘P2’, sometimes fails to call the person as he is only able to hear the alarm, from a certain distance.

- **<u>Q</u>)** Find the probability that ‘P1’ is true (P1 has called ‘gfg’), ‘P2’ is true (P2 has called person) when the alarm ‘A’ rang, but no burglary ‘B’ and fire ‘F’ has occurred.

- => **P (P1, P2, A, ~B, ~F)** [where- P1, P2 & A are ‘true’ events and ‘~B’ & ‘~F’ are ‘false’ events]
- **Note:** The values mentioned below are neither calculated nor computed. They have observed values]

Burglary ‘B’ –

- **P (B=T) = 0.001** (‘B’ is true i.e burglary has occurred)
- **P (B=F) = 0.999** (‘B’ is false i.e burglary has not occurred)

Fire ‘F’ –

- **P (F=T) = 0.002** (‘F’ is true i.e fire has occurred)
- **P (F=F) = 0.998** (‘F’ is false i.e fire has not occurred)

- ***Alarm 'A' –***

B	F	P (A=T)	P (A=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

•The alarm 'A' node can be 'true' or 'false' (i.e may have rung or may not have rung).
• It has two parent nodes burglary 'B' and fire 'F' which can be 'true' or 'false' (i.e may have occurred or may not have occurred) depending upon different conditions.

- ***Person ‘P1’ –***

A	P (P1=T)	P (P1=F)
T	<u>**0.95**</u>	0.05
F	0.05	0.95

•The person ‘P1’ node can be ‘true’ or ‘false’ (i.e may have called the person ‘gfg’ or not) . It has a parent node, the alarm ‘A’, which can be ‘true’ or ‘false’ (i.e may have rung or may not have rung ,upon burglary ‘B’ or fire ‘F’).

- ***Person ‘P2’ –***

A	P (P2=T)	P (P2=F)
T	0.80	0.20
F	0.01	0.99

•The person ‘P2’ node can be ‘true’ or false’ (i.e may have called the person or not).

•It has a parent node, the alarm ‘A’, which can be ‘true’ or ‘false’ (i.e may have rung or may not have rung, upon burglary ‘B’ or fire ‘F’).

Solution:

From the observed probabilistic scan, we can deduce –

P (P1, P2, A, ~B, ~F)

= P (P1/A) * P (P2/A) * P (A/~B~F) * P (~B) * P (~F)

= 0.95 * 0.80 * 0.001 * 0.999 * 0.998

= 0.00075