Artificial Intelligence(AI)

CS6659 - AI Notes

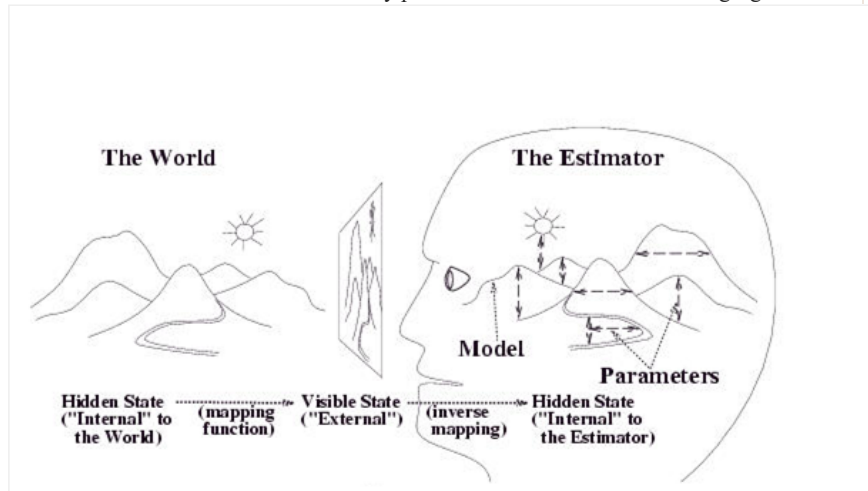Syllabus | Unit -I | Unit -II | Unit-III | Unit - IV | Unit - V | Lecture Videos - Collection 1

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Bayesian Network

Bayesian network reflects the states of some part of the world that is being modeled and it describes how those states are related by probabilities.Consider the following figure

There is an agent which recognizes a world,and it perceives that the world has mountains,roads,sun and so on.The world's model has been recognized with the help of knowledge representation.Now,how can an agent says that there will be a possibility for the occurrence of accidents on bend road.In that case probabilities comes in.Is there any belief for the statements delivered by an agent,in that case there is a need of Bayesian network which purely works based on conditional probability. Well, typically some states will tend to occur more frequently when other states are present. Thus, if you are sick, the chances of a runny nose are higher. If it is cloudy, the chances of rain are higher, and so on. Here is a simple Bayes net that illustrates these concepts. In this simple world, let us say the weather can have three states: sunny, cloudy, or rainy, also that the grass can be wet or dry, and that the sprinkler can be on or off. Now there are some causal links in this world. If it is rainy, then it will make the grass wet directly. But if it is sunny for a long time, that too can make the grass wet, indirectly, by causing us to turn on the sprinkler.
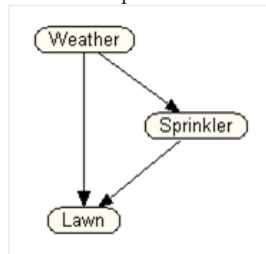
"if the lawn is wet, what are the chances it was caused by rain or by the sprinkler", and "if the chance of rain increases, how does that affect my having to budget time for watering the lawn".
In this case,conditional probability helps to predict the cause for the lawn wetness.let's have a short discussion about conditional probability rule.
$P(A|B) = P(A \cap B) / P(B)$

In words: the probability of event A given that event B happened is equal to the intersection of the two events divided by the probability of B.
we will use the following simple medical diagnosis problem.

Example problem:

Suppose we want to use the diagnostic assistant to diagnose whether there is a fire in a building based on noisy sensor information and possibly conflicting explanations of what could be going on. The agent receives a report about whether everyone is leaving the building. Suppose the report sensor is noisy: It sometimes reports leaving when there is no exodus (a false positive), and it sometimes does not report when everyone is leaving (a false negative). Suppose the fire alarm going off can cause the leaving, but this is not a deterministic relationship. Either tampering or fire could affect the alarm. Fire also causes smoke to rise from the building.
Suppose we use the following variables, all of which are Boolean, in the following order:

- *Tampering* is true when there is tampering with the alarm.
- *Fire* is true when there is a fire.
- *Alarm* is true when the alarm sounds.
- *Smoke* is true when there is smoke.
- *Leaving* is true if there are many people leaving the building at once.
- *Report* is true if there is a report given by someone of people leaving. *Report* is false if there is no report of leaving.

The variable *Report* denotes the sensor report that people are leaving. This information is unreliable because the person issuing such a report could be playing a practical joke, or no one who could have given such a report may have been paying attention. This variable is introduced to allow conditioning on unreliable sensor data. The agent knows what the sensor reports, but it only has unreliable evidence about people leaving the building. As 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*.
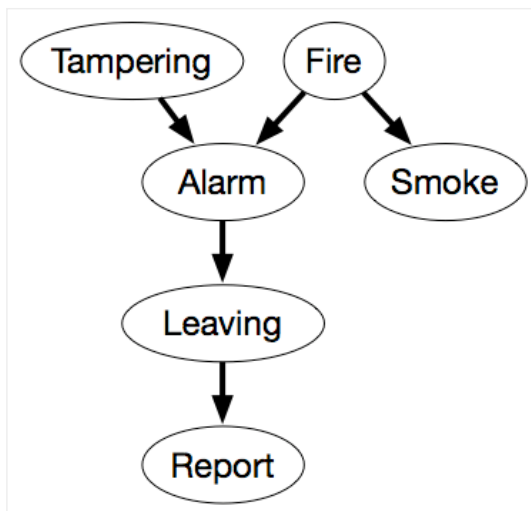
This network represents the factorization

P(Tampering,Fire,Alarm,Smoke,Leaving,Report)

$$= \begin{array}{l} P(Tampering) \times P(Fire) \\ \times P(Alarm|Tampering,Fire) \\ \times P(Smoke|Fire) \times P(Leaving|Alarm) \\ \times P(Report|Leaving). \end{array}$$

We also must define the domain of each variable. Assume that the variables are Boolean; that is, they have domain *{true,false}*. We use the lower-case variant of the variable to represent the true value and use negation for the false value. Thus, for example, *Tampering=true* is written as *tampering*, and *Tampering=false* is written as *¬tampering*.

The examples that follow assume the following conditional probabilities:
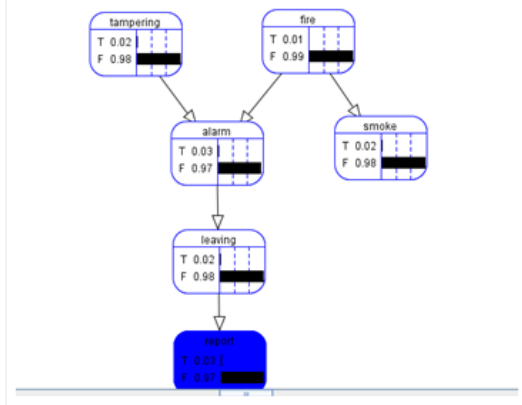
The following conditional probabilities follow from the model,
P(tampering) = 0.02
P(fire) = 0.01
P(report) = 0.03
P(smoke) = 0.02
P(alarm) = 0.03
P(leaving) = 0.02

Now ,observe the values by making Tampering as **true**

P(alarm|tampering) = 0.85
P(leaving|alarm) = 0.74
P(report|leaving) = 0.56
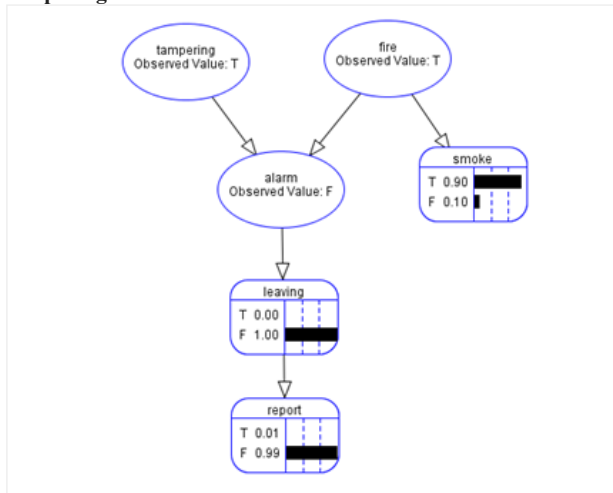
Let us make the fire as true along with tampering,
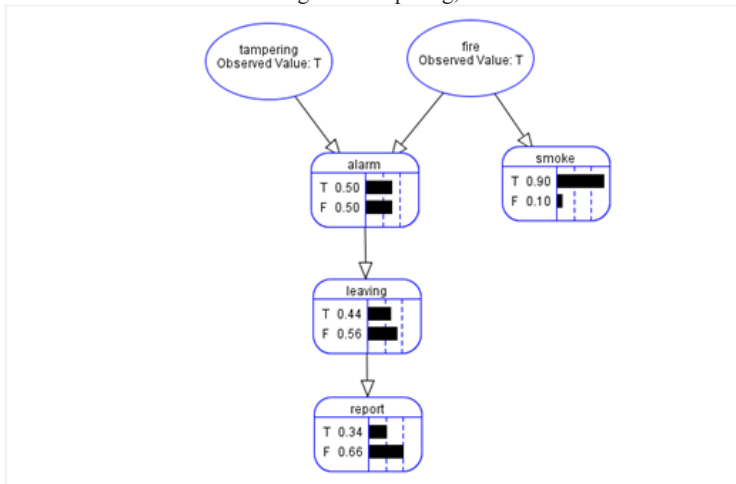
P(alarm|tampering ^ fire) = 0.50
P(leaving|alarm) = 0.44
P(report|leaving) = 0.34

As we all know that the leaving and report is depend on alarm and conditionally independent of Tampering and Smoke.To prove this let us make the **alarm** as false given **tampering and fire**

From the figure it is clear that the leaving and report is depend on **alarm** not on **fire and tampering.**By this way we can conclude with the following probability assumptions

P(tampering) = 0.02
P(fire) = 0.01
P(alarm | fire ∧tampering) = 0.5
P(alarm | fire ∧¬tampering) = 0.99
P(alarm | ¬fire ∧tampering) = 0.85
P(alarm | ¬fire ∧¬tampering) = 0.0001
P(smoke | fire) = 0.9
P(smoke | ¬fire) = 0.01
P(leaving | alarm) = 0.88
P(leaving | ¬alarm) = 0.001
P(report | leaving) = 0.75
P(report | ¬leaving) = 0.01

This example illustrates how the belief net independence assumption gives commonsense conclusions and also demonstrates how explaining away is a consequence of the independence assumption of a belief network. Bayesian learning methods are firmly based on probability theory and exploit advanced methods developed in statistics.Naïve Bayes is a simple generative model that works fairly well in practice.A Bayesian network allows specifying a limited set of dependencies using a directed graph.Inference algorithms allow determining the probability of values for query variables given values for evidence variables.

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