The tool we will use to work with probabilistic reasoning is called a **Bayesian Network**.
This consists of two major components:

1. Directed Acyclic Graph shows casualty
2. Numbers/Nodes represent probability

Notation:

- Variable — X
- Value — x
- Variable Probability Distribution — Pr(x) = Pr(X=x)
- Set of Variables — X
- Instantiation — x
- World Probability Distribution — Pr(X) = truth table

Remember that if $Pr(\alpha|\beta, \gamma) = Pr(\alpha|\gamma)$, then α & β are independent given γ
We can apply the same idea to sets of variables:
X and Y are independent given Z if Pr(x|y, z) = Pr(x|z)
We write this as I(X, Z, Y)

Consider the following

$![DirectedAcyclicGraph(G)](https : //paper - attachments.dropbox.com/s_13F2D47E7D3DCA10BE34C69E62E331D2224F9C5F91BEA8639D242F2792B86517_15901156979$
$drawing.jpg)$

Logic

The alarm is triggered by burglary or earthquake. A radio report is caused by an earthquake. A call from the neighbor may come post-alarm.

Independence

R & C are independent given A — I(R, A, C)
E & B are independent — I(E, ϕ, B)

This can be much more efficient than a table.
The independence and parameters uniquely identify the graph.

We introduce a few terms:

- Parents(V) — the nodes pointing through V via an edge
  Parents(A) = {E, B} & Parents(R) = {E}
- Descendants(V) — the nodes reachable by V
  Descendants(E) = {R, A, C} & Descendants(B) = {A, C} & Descendants(X) = {}
- Non-Descendants(V) — the nodes unreachable from V, excluding the self & parents
  Non-descendants(A) = {R} & Non-descendants(E) = {B}

We call these independence statements the **Marcovion Assumptions**
 ≡ all the defined independence statements of a Bayesian Network
 These are of the form I(V, Parents(V), Non-Descendants(V))
Marcov(G) = { I(C, A, BE), I(R, E, ABC), I(A, BE, R), I(B, ϕ, ER), I(E, ϕ, B) }

We can parametrize the structure by assigning weight to the connections.

![]($https : //paper -$
$attachments.dropbox.com/s_13F2D47E7D3DCA10BE34C69E62E331D2224F9C5F91BEA8639D242F2792B86517_15901172082$
$Shot + 2020 - 05 - 21 + at + 8.13.19 + PM.png$)

Note that $Pr(\neg d, b, \neg c) = \theta_{\{}\neg d|b, \neg c\}$

Consider an arbitrary row abcde

$Pr(abcde) = \theta_a\ \theta_{b|a}\ \theta_{c|a}\ \theta_{d|bc}\ \theta_{e|c} = 0.7$
$Pr(ab\neg cd\neg e) = \theta_a\ \theta b|a\ \theta_{\neg c|a}\ \theta_{d|b\neg c}\ \theta_{\neg e|c} = 0.216$
$Pr(\neg(abcde)) = \theta_{\neg a}\ \theta_{\neg b|\neg a}\ \theta_{\neg c|\neg a}\ \theta_{\neg d|\neg b\neg c}\ \theta_{\neg e|\neg c} = 0.09$

We can evaluate the independence of any two nodes are independent given a third by

Deseperation

This uses an expansion on Markov's much more efficient than probability theory.
If setting Z blocks paths x→y, x & y are d-separated given Z
There are three ways for a node to be connected in a path:

- sequential $\equiv \rightarrow w \rightarrow$
- divergent $\equiv \leftarrow w \rightarrow$
- convergent $\equiv \rightarrow w \leftarrow$

These are each treated differently:

$\neg[](https : //paper -$
$attachments.dropbox.com/s_1 3F2D47E7D3DCA10BE34C69E62E331D2224F9C5F91BEA8639D242F2792B86517_1 590118451 7$
$drawing + 2.jpg)$

We can clarify by giving an example:

$![](https://paper-attachments.dropbox.com/s_13F2D47E7D3DCA10BE34C69E62E331D2224F9C5F91BEA8639D242F2792B86517_159011921033$
$drawing+4.jpg)$