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

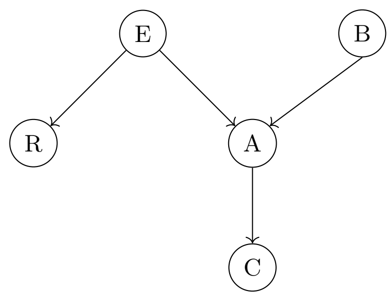
1. Directed Acyclic Graph shows casualty
2. Numbers/Nodes represent probability

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:



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)

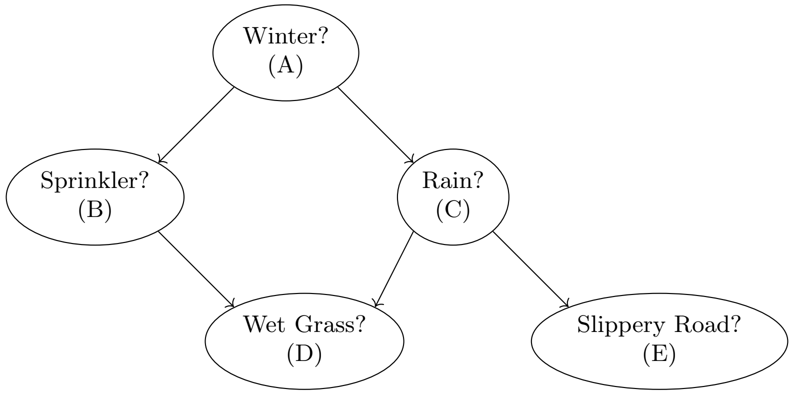
This can be much more efficient than a table.
The independence and parameters uniquely identify the graph.

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.



A	θ_A
1	0.6
0	0.4

A	B	$\theta_{B\|A}$
1	1	0.2
1	0	0.8
0	1	0.75
0	0	0.25

A	C	$\theta_{C\|A}$
1	1	0.8
1	0	0.2
0	1	0.1
0	0	0.9

B	C	D	$\theta_{D\|B,C}$
1	1	1	0.95
1	1	0	0.05
1	0	1	0.9
1	0	0	0.1
0	1	1	0.8
0	1	0	0.2
0	0	1	0
0	0	0	1

C	E	$\theta_{E\|C}$
1	1	0.7
1	0	0.3
0	1	0
0	0	1

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

Consider an arbitrary row abcde

$Pr(abcde) = \theta_a\ \theta_{b|a}\ \theta_{c|a}\ \theta_{d|bc}\ \theta_{e|c} = 0.7$

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

$Pr(\neg(abcde)) = \theta_{\neg a}\ \theta_{\neg b|\neg a}\ \theta_{\neg c|\neg a}\ \theta_{\neg d|\neg b\neg c}\ \theta_{\neg e|\neg c} = 0.09$

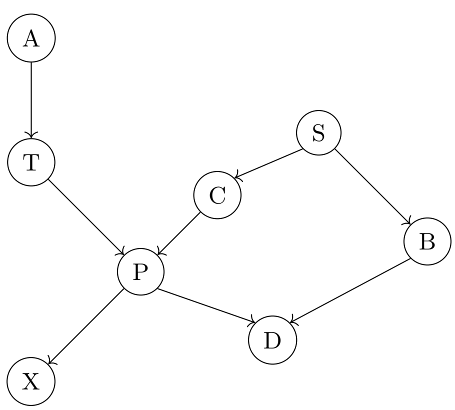
We can evaluate the independence of any two nodes are independent given a third by

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, treated as follows:

- sequential $\equiv \rightarrow w \rightarrow$ is blocked iff w $\in$ **Z**
- divergent $\equiv \leftarrow w \rightarrow$ is blocked iff w $\in$ **Z**
- convergent $\equiv \rightarrow w \leftarrow$ is blocked iff w & Decendants(w) $\notin$ **Z**

We can clarify by giving an example:



dsep(C, S, B)?
→ open(BSC)? false.
→ open(CPDV)?
⟶ open(SPD)? true.
⟶ open(PDS)? false.
⟹ dsep(C, S, B) = true.