Bayesian Networks
Part 4 of 4
Model Structure

Based on:
Risk Assessment and Decision Analysis with Bayesian Networks
Norman Fenton & Martin Neil, CRC Press, 2013, pp 192..197

Mountain pass

◊ Want to travel from home to an appointment in another town

Mountain pass – 2

◊ Want to travel from home to an appointment in another town

◊ Can travel either by car or by train

Mountain pass – 3

◊ Want to travel from home to an appointment in another town

◊ Can travel either by car or by train

◊ Car trip goes through a mountain pass that may be closed by bad weather

Mountain pass – 4

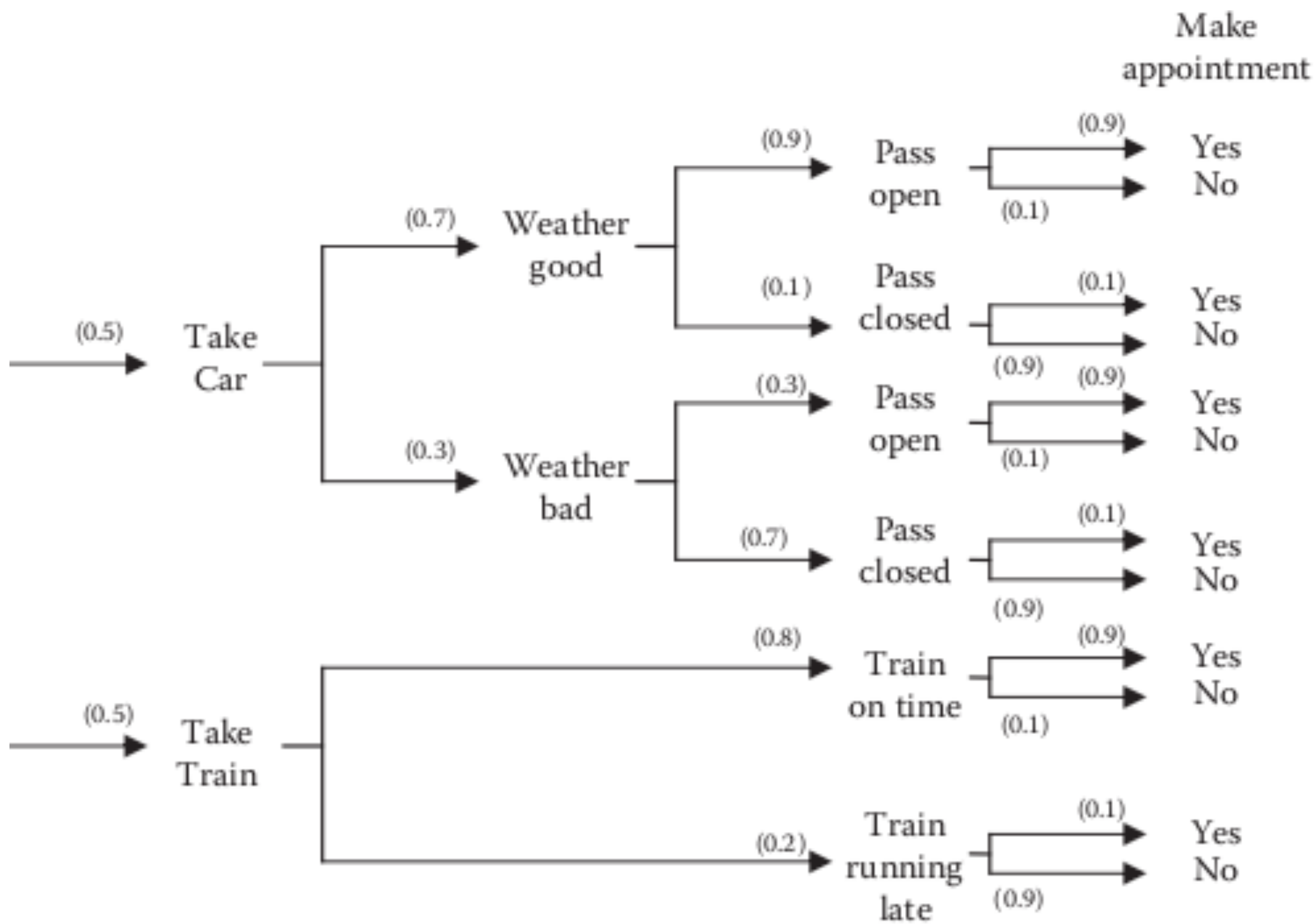
- Want to travel from home to an appointment in another town
- Can travel either by car or by train
- Car trip goes through a mountain pass that may be closed by bad weather
- Train is not affected by bad weather or the mountain pass conditions but may not run on schedule

Mountain pass – 5

- Want to travel from home to an appointment in another town
- Can travel either by car or by train
- Car trip goes through a mountain pass that may be closed by bad weather
- Train is not affected by bad weather or the mountain pass conditions but may not run on schedule

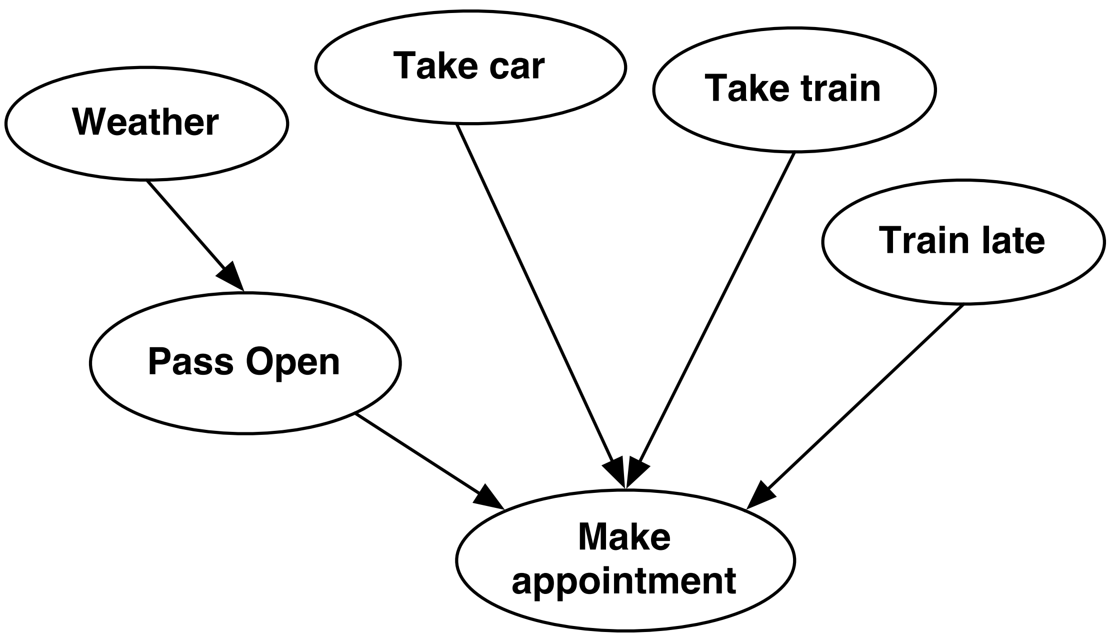
  - **What is likelihood of arriving on time for the appointment?**

Event tree for mountain pass



Model 1

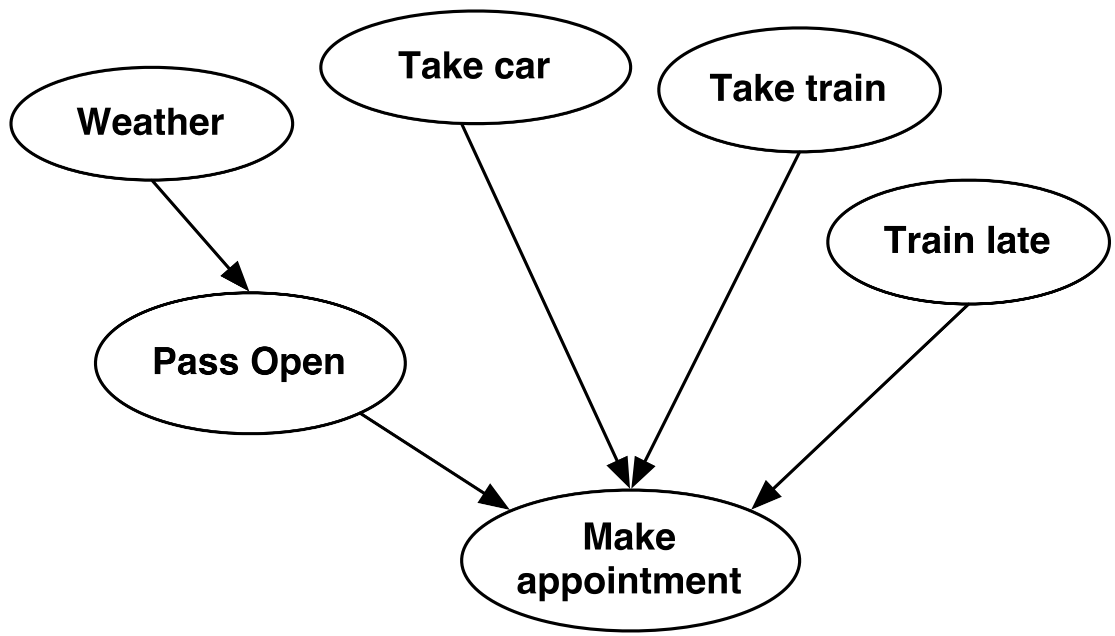
» **What is wrong with this model?**



Model 1 – 2

» What is wrong with this model?

> Make appointment has many impossible states

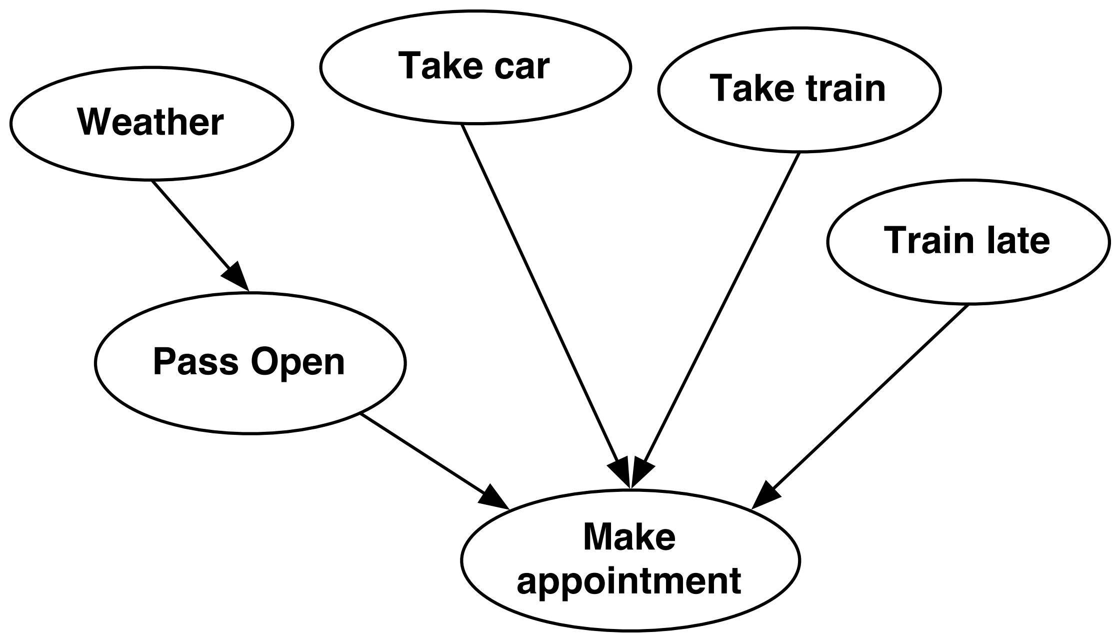


Model 1 – 2

» What is wrong with this model?

> Make appointment has many impossible states

– Complex node probability table (NPT)



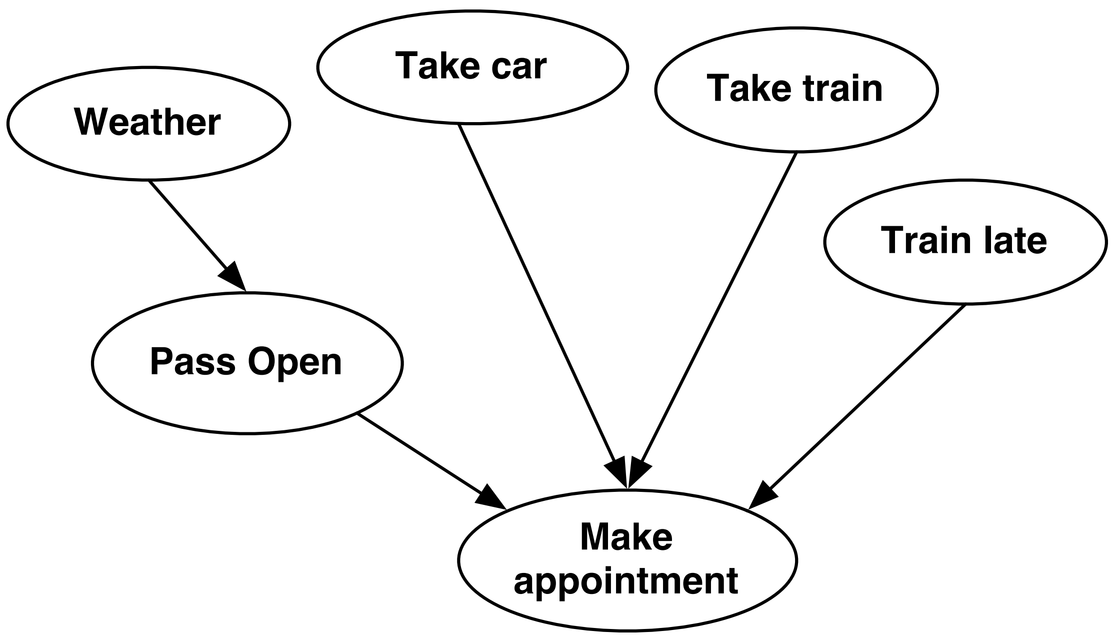
Model 1 – 3

» What is wrong with this model?

> Make appointment has many impossible states

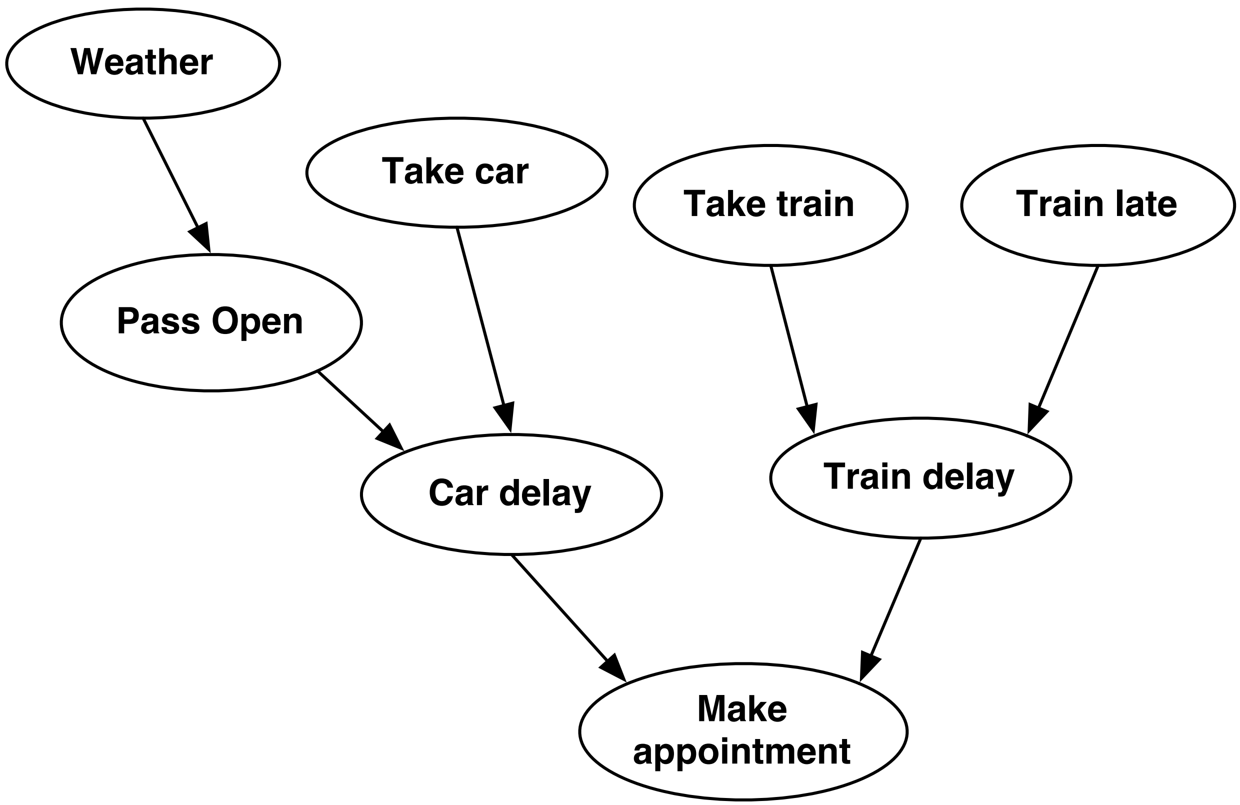
– Complex node probability table (NPT)

> No mutual exclusion between taking car or train



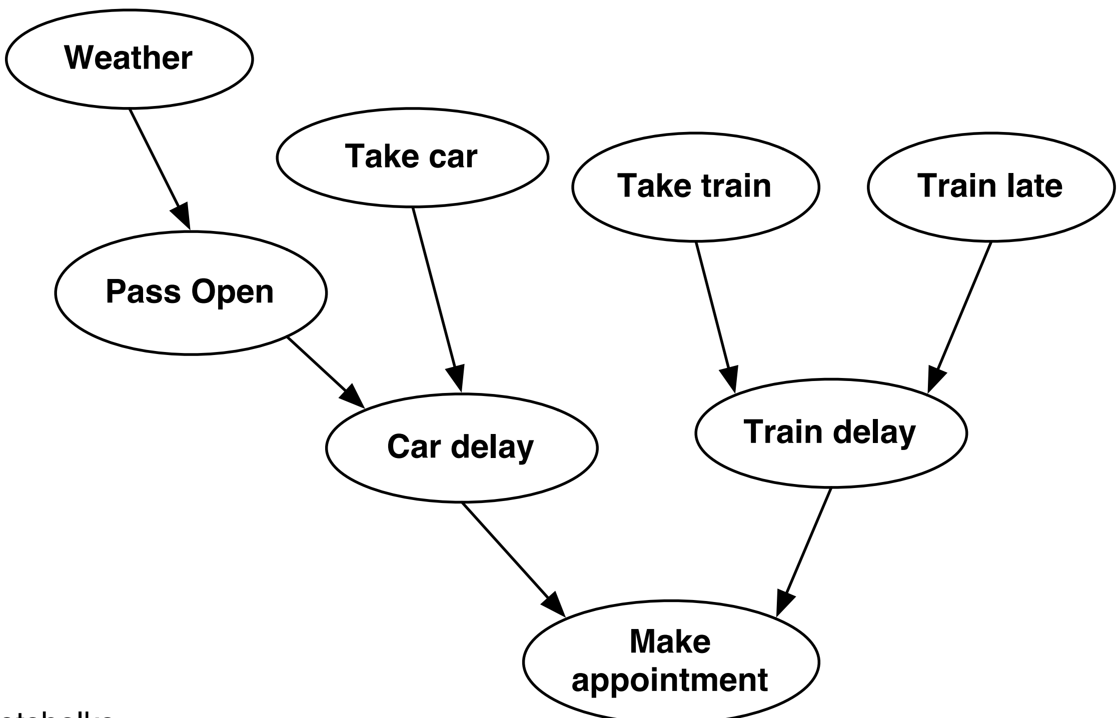
Model 2

» Are the problems alleviated? How?
  > Make appointment has many impossible states
  > No mutual exclusion between taking car or train



Model 2 – 2

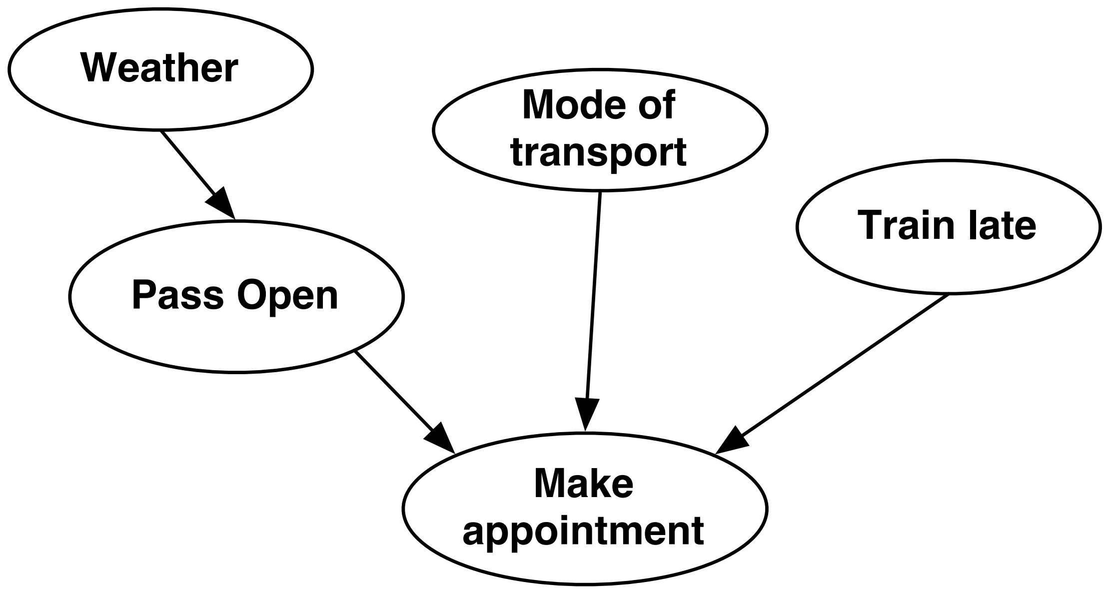
- » Are the problems alleviated alleviated? How?
  - > Make appointment has many impossible states
    - – Simpler node probability table (NPT)
  - > No mutual exclusion between taking car or train
    - – Not alleviated



Model 3

◊ Mutual exclusion solved using Mode of transport node

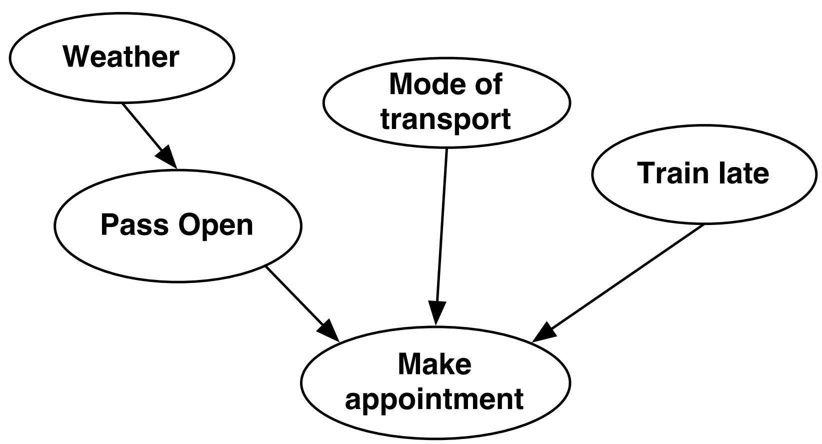
» **NPT for Mode of transport has probability for taking car and train**



Model 3 – 2

> **NPT for make appointment**
  – **Selects left or right causal pathway depending upon mode of transport**

Mode of Transport	Train				Car			
Train Late?	False		True		False		True	
Pass Open?	Open	Closed	Open	Closed	Open	Closed	Open	Closed
False	0.1	0.1	0.9	0.9	0.1	0.9	0.1	0.9
True	0.9	0.9	0.1	0.1	0.9	0.1	0.9	0.1



Causal pathways

◊ Not all mutual exclusion problems can be solved as simply as in the mountain pass problem

Causal pathways – 2

- Not all mutual exclusion problems can be solved as simply as in the mountain pass problem
  - **What about the situation where there are two or more mutually exclusive states, each belonging to a different causal pathway**

Causal pathways – 3

◊ Not all mutual exclusion problems can be solved as simply as in the mountain pass problem

» **What about the situation where there are two or more mutually exclusive states, each belonging to a different causal pathway**

> **Merging the causal pathways into a single node may**

– **Detract from the semantics of the model**

Causal pathways – 4

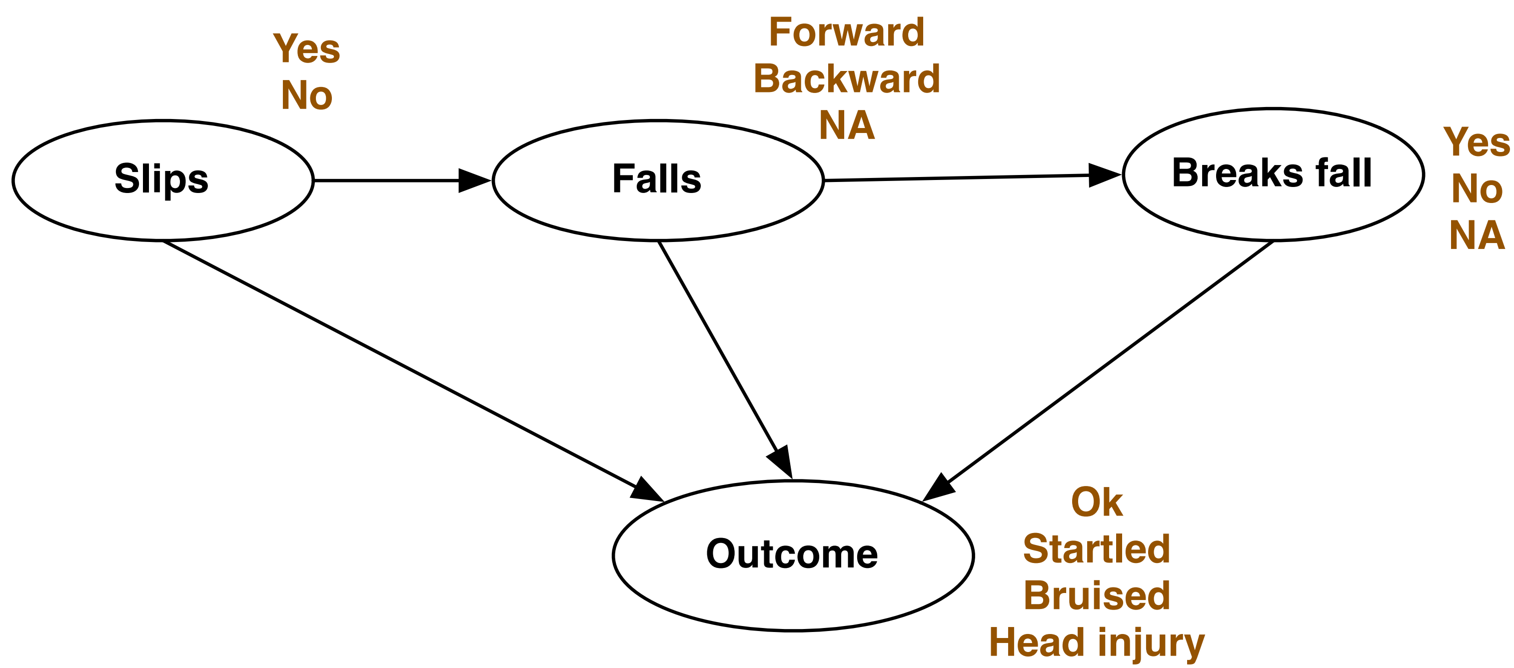
- ◊ Not all mutual exclusion problems can be solved as simply as in the mountain pass problem
  - » **What about the situation where there are two or more mutually exclusive states, each belonging to a different causal pathway**
    - > **Merging the causal pathways into a single node may**
      - – **Detract from the semantics of the model**
      - – **Make elicitation and communication difficult**

Slip & fall

◊ Single node for all the outcomes (pathways)

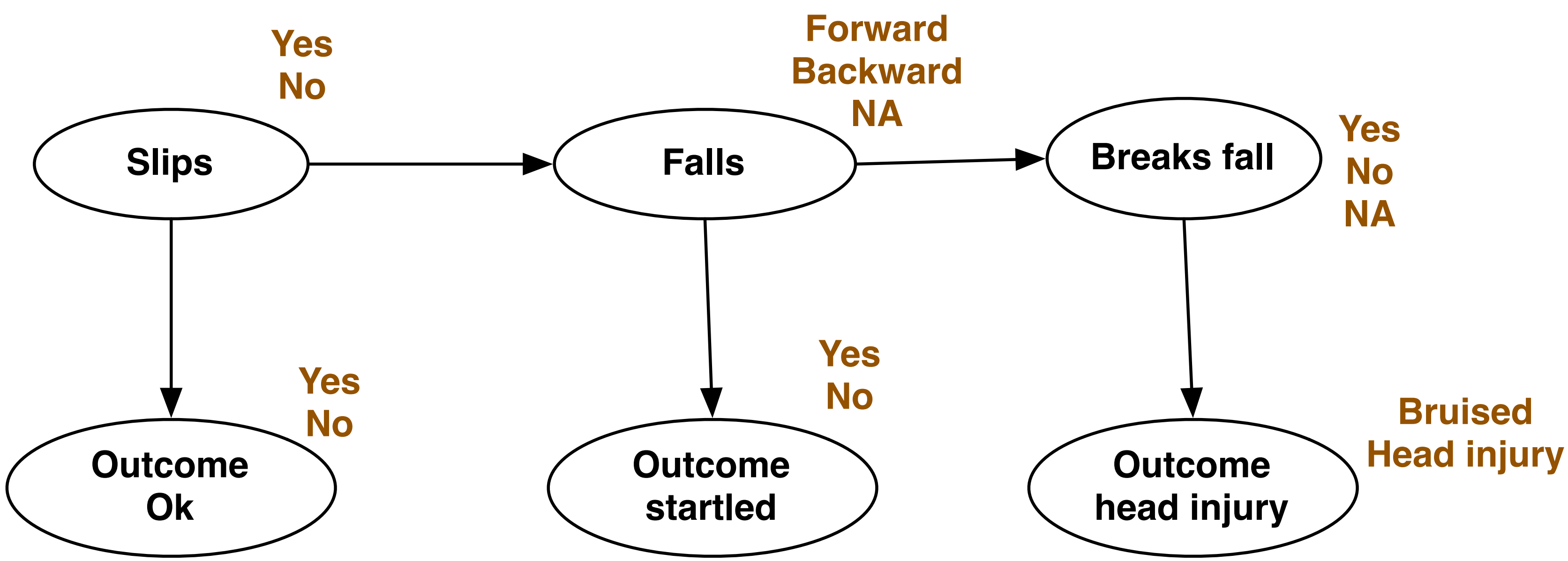
◊ Total number of NPT entries is 89

» **Slips (2)** **Falls (6)** **Breaks fall (9)** **Outcome (72)**



Slip & fall– 2

- Separate nodes for different outcomes (pathways)
- Total number of NPT entries is 33
  - No table has more than 9 entries
    - Much clearer to understand and deal with



Blood on shirt

◊ In a murder trial a central piece of evidence is the existence of blood found on the defendant's shirt collar

Blood on shirt – 2

- In a murder trial a central piece of evidence is the existence of blood found on the defendant’s shirt collar
- It could have come from the victim, if the defendant really was present during the murder

Blood on shirt – 3

- In a murder trial a central piece of evidence is the existence of blood found on the defendant's shirt collar
- It could have come from the victim, if the defendant really was present during the murder
- Or the defendant who may have cut themselves shaving

Blood on shirt – 4

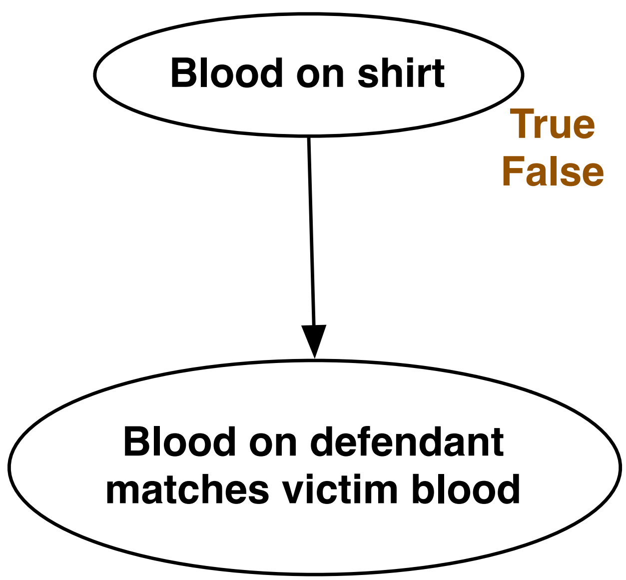
- In a murder trial a central piece of evidence is the existence of blood found on the defendant's shirt collar
- It could have come from the victim, if the defendant really was present during the murder
- Or the defendant who may have cut themselves shaving
- There is a strong assumption that these two events are mutually exclusive

Blood on shirt – 5

- In a murder trial a central piece of evidence is the existence of blood found on the defendant’s shirt collar
- It could have come from the victim, if the defendant really was present during the murder
- Or the defendant who may have cut themselves shaving
- There is a strong assumption that these two events are mutually exclusive
  - **If the blood came from one it cannot have come from the other**

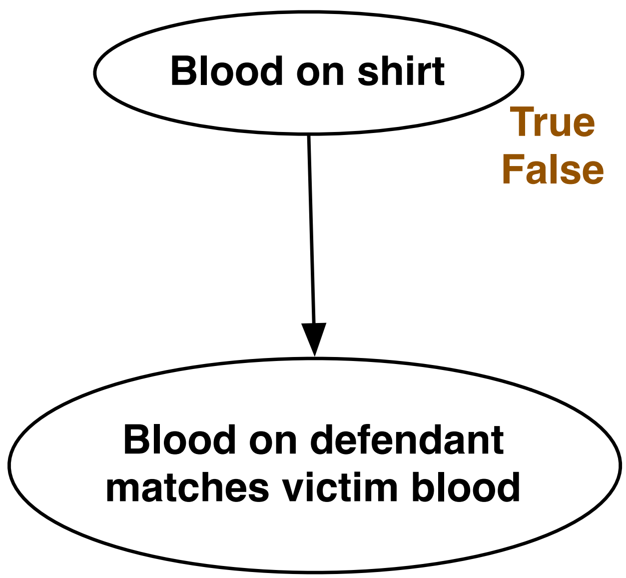
Blood on shirt – model 1

◊ Single node used for mutual exclusion



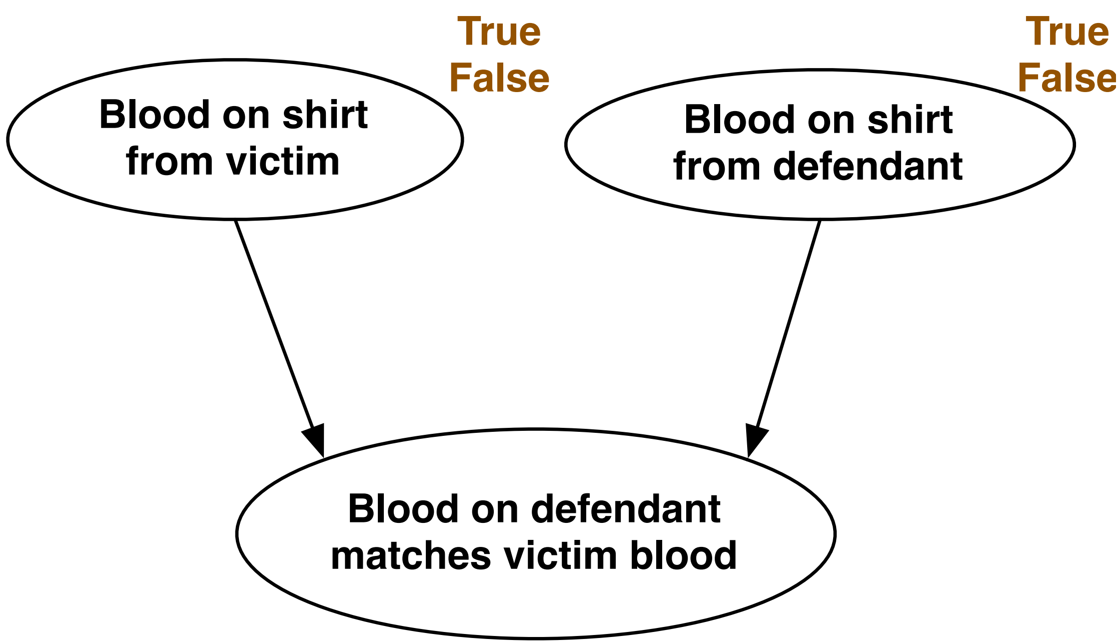
Blood on shirt – model 1 – 2

- Single node used for mutual exclusion
  - **Problem is that there are complex, distinct pathways involving different evidence leading to alternate hypotheses**



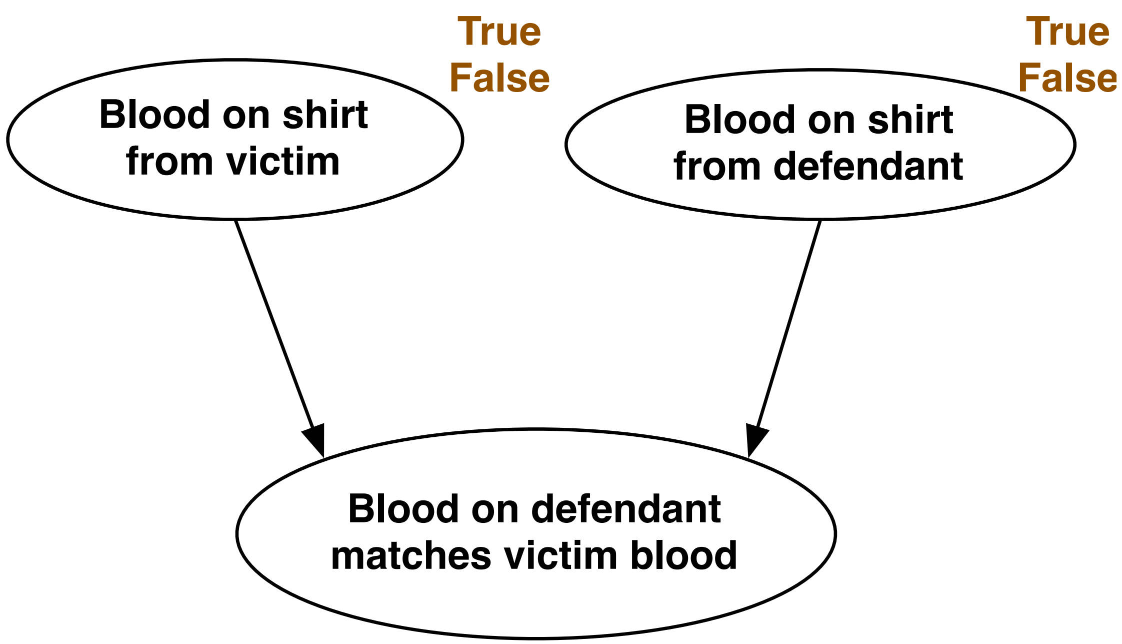
Blood on shirt – model 2

- Separate pathways



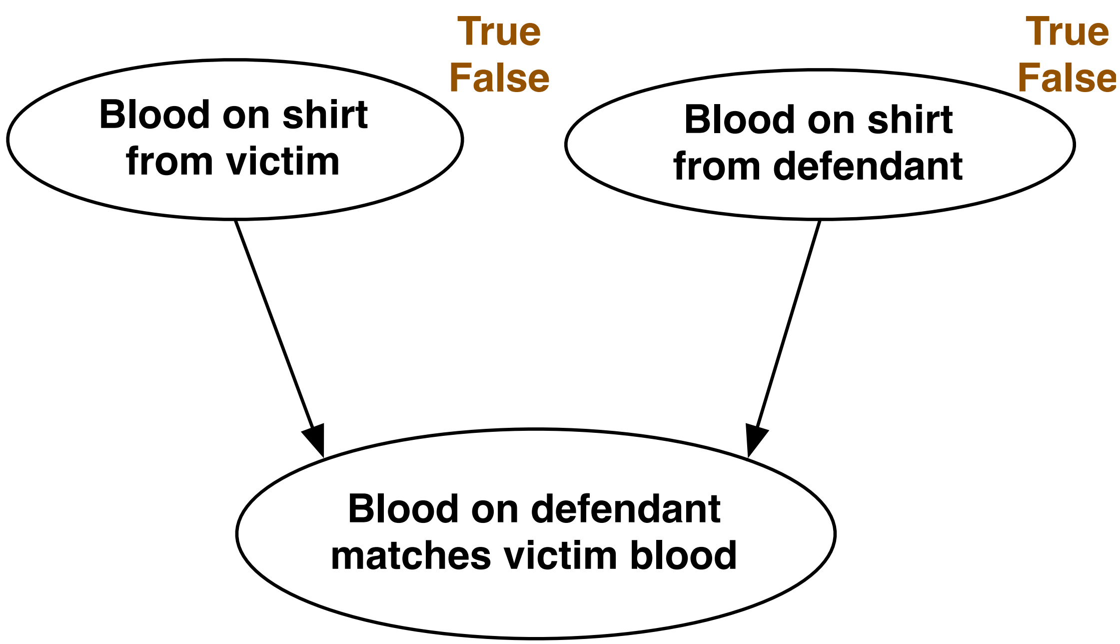
Blood on shirt – model 2 – 2

- Separate pathways
  - **Does not enforce mutual exclusion**



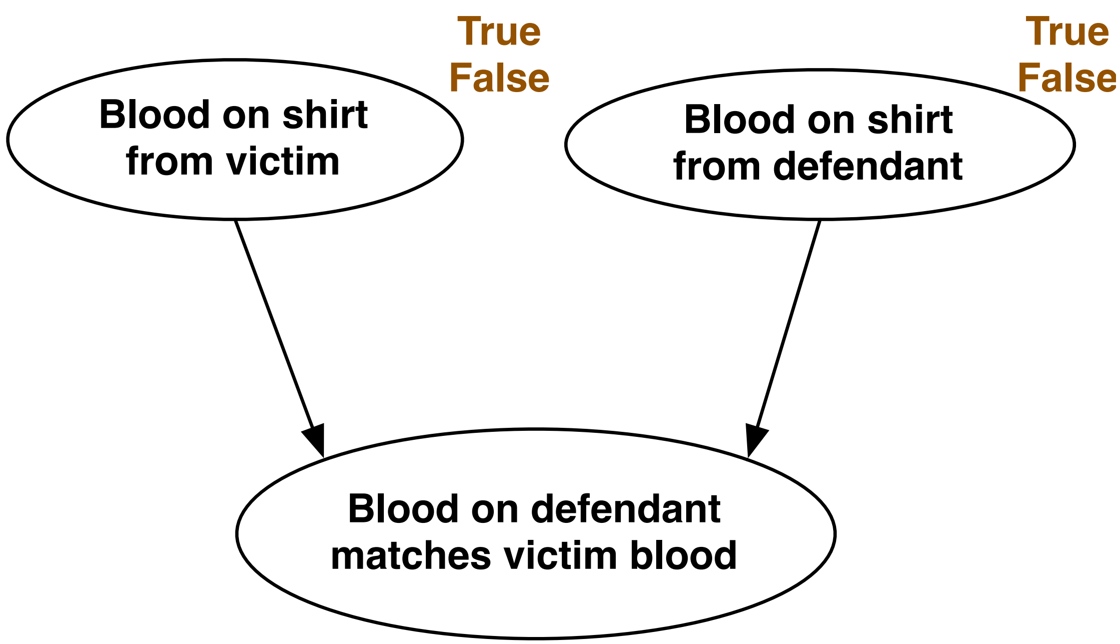
Blood on shirt – model 2 – 3

- Separate pathways
  - **Do not enforce mutual exclusion**
    - **Could add a link between top nodes**



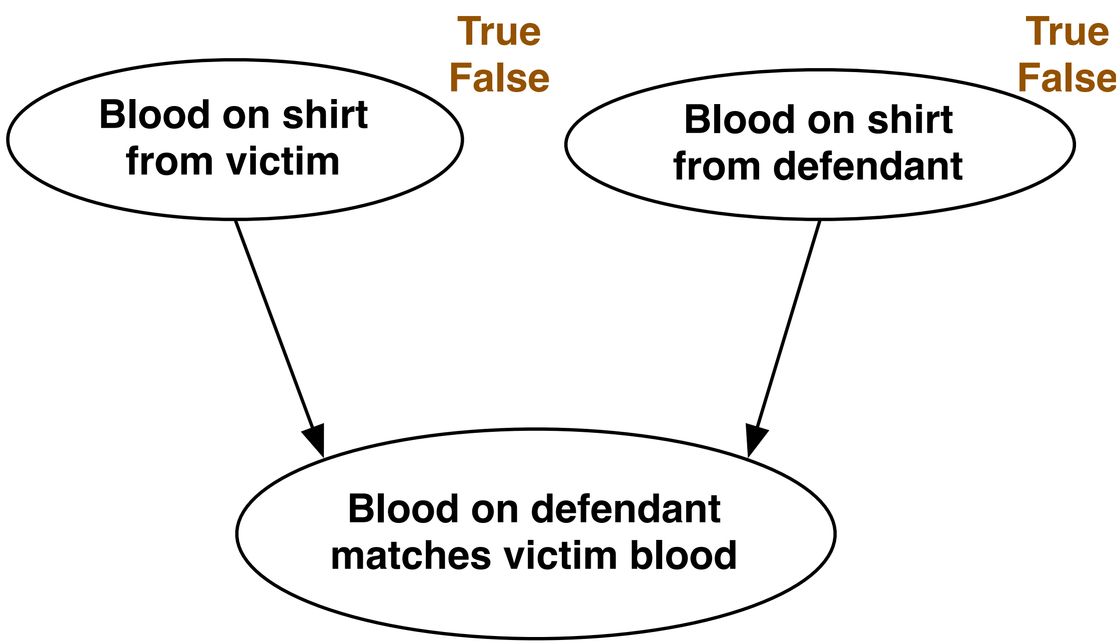
Blood on shirt – model 2 – 4

- Separate pathways
  - **Do not enforce mutual exclusion**
    - **Could add a link between top nodes**
      - **Artificial dependency**



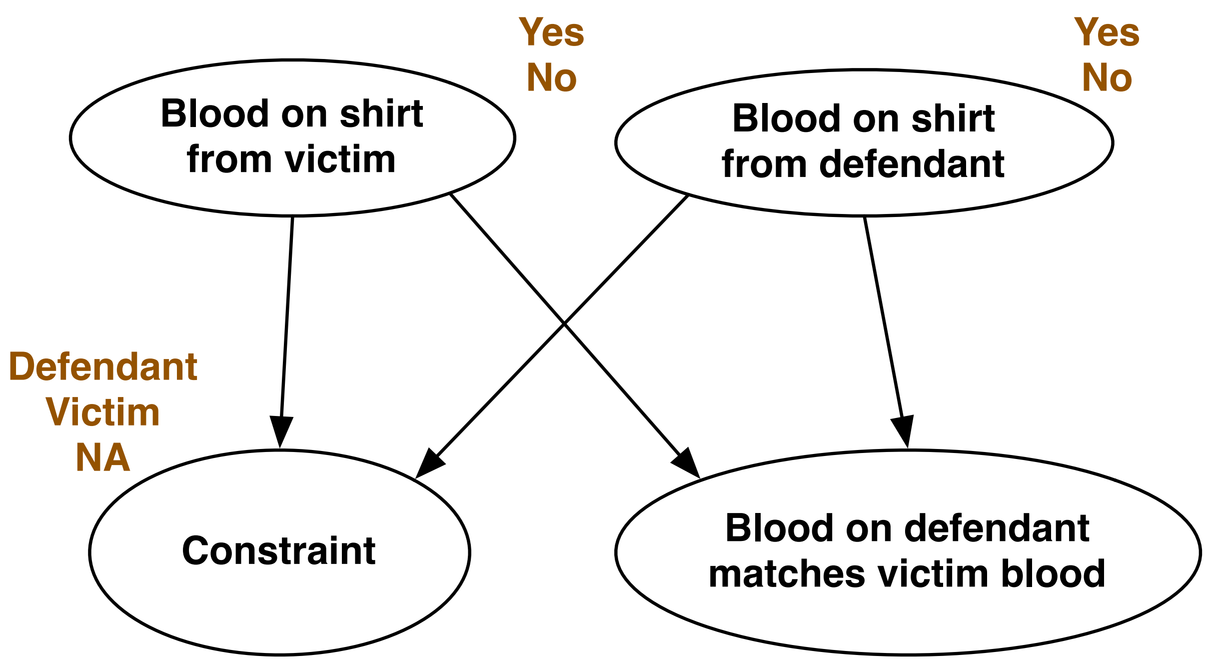
Blood on shirt – model 2 – 5

- Separate pathways
  - Do not enforce mutual exclusion
    - Could add a link between top nodes
      - Artificial dependency
      - Solution fails with more than 2 causes



Blood on shirt – model 3

◊ Solution for an arbitrary number of mutual exclusive causes



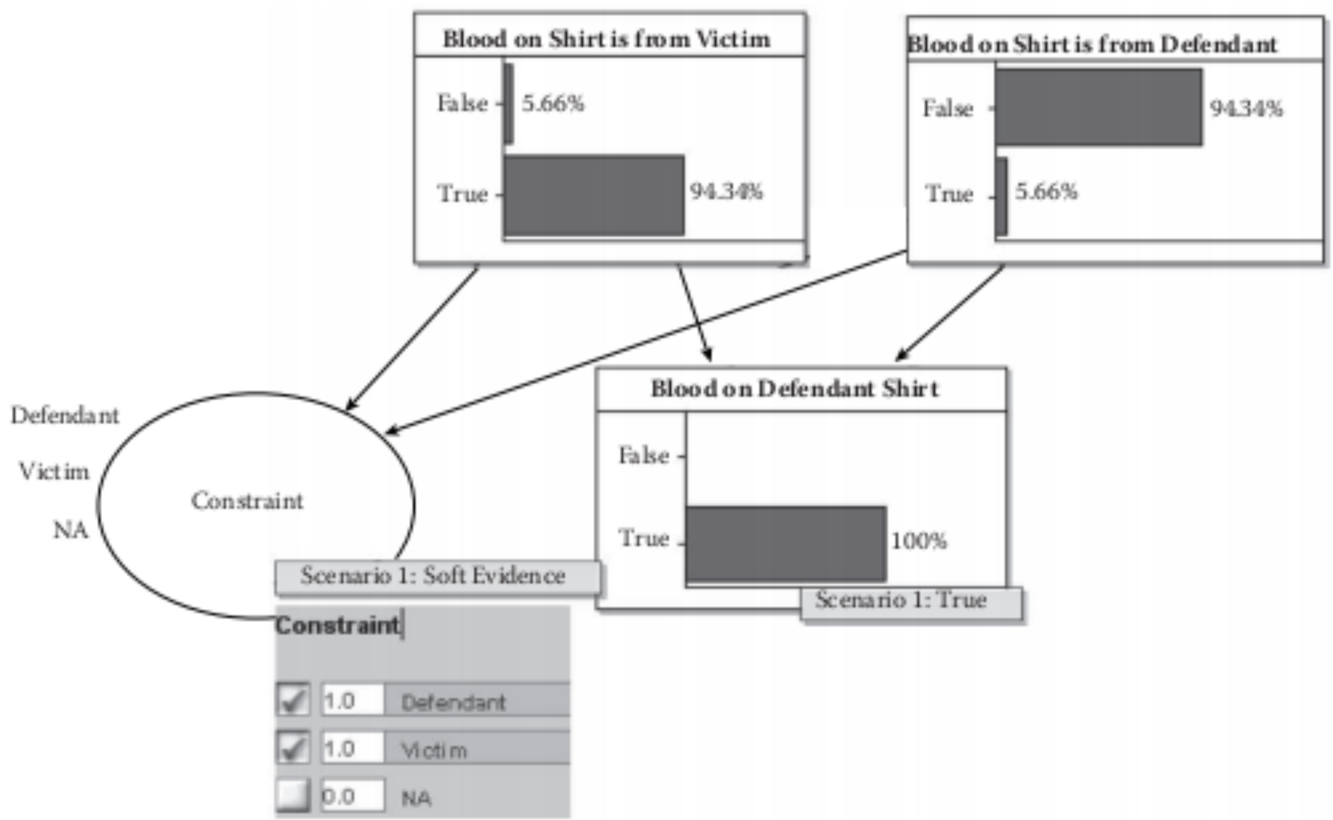
Blood on shirt – model 3 – 2

- NPT for Constraint
  - **NA state is for combinations of states we think are impossible**

Blood on Shirt Is from Defendant	False		True	
Blood on Shirt Is from Victim	False	True	False	True
Defendant	0.0	0.0	1.0	0.0
Victim	0.0	1.0	0.0	0.0
NA	1.0	0.0	0.0	1.0

Blood on shirt – model 3 – 3

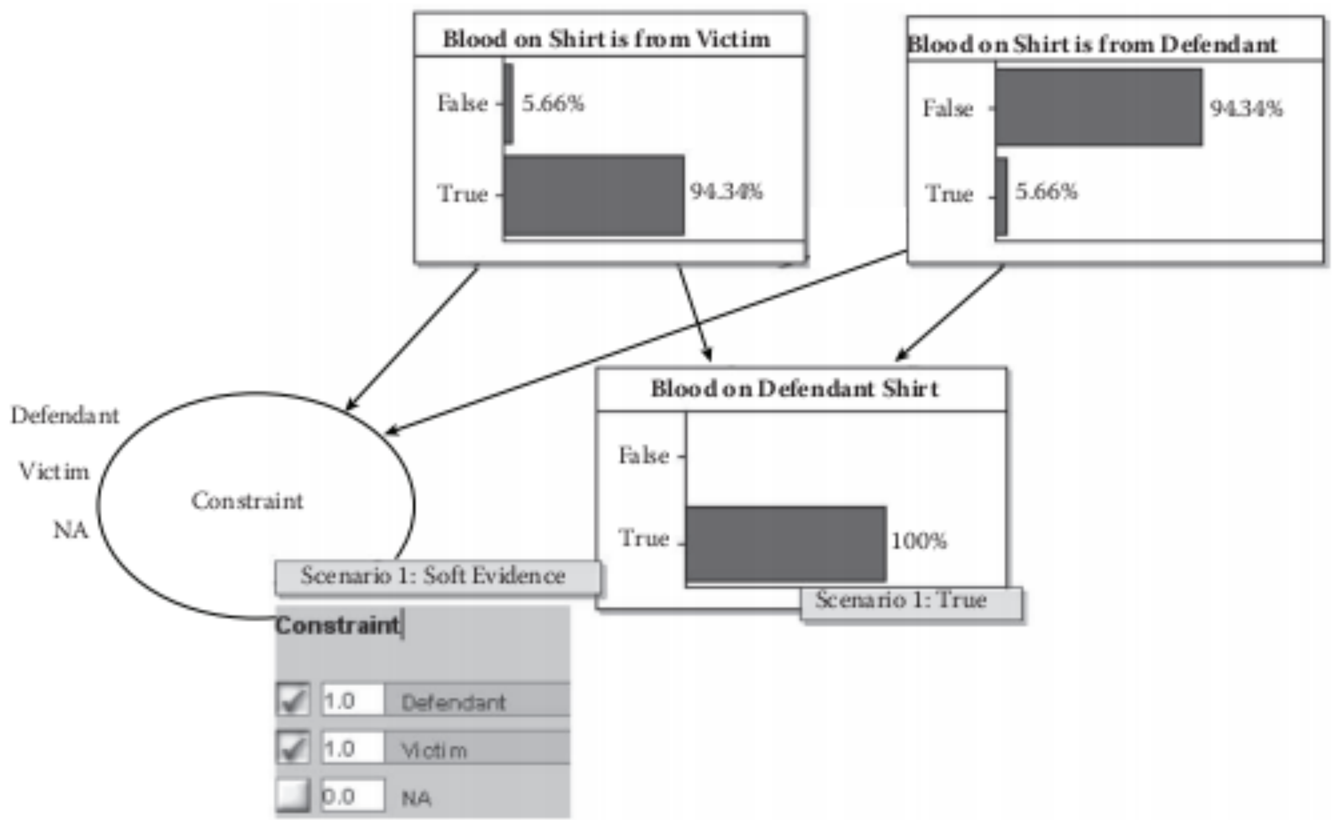
◊ To get model to work as required, set the soft evidence on the constraint node to ensure that NA is impossible



Blood on shirt – model 3 – 4

◊ To get model to work as required, set the soft evidence on the constraint node to ensure that NA is impossible

» **Meaning that the impossible states can never be observed**



Hard evidence

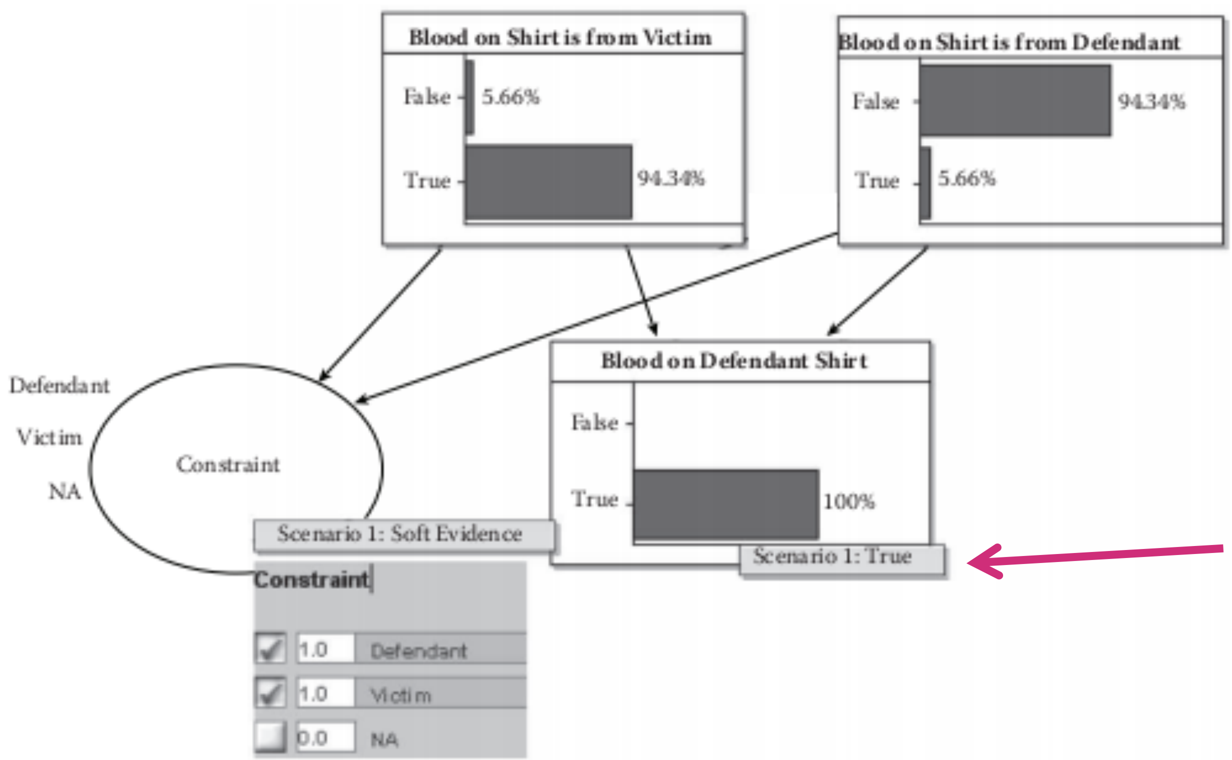
- Suppose we know for certain that Norman is late on a particular day

Hard evidence – 2

- Suppose we know for certain that Norman is late on a particular day
  - **Then P(Norman_late = true) = 1**

Hard evidence – 3

- We know for certain that Norman is late on a particular day
  - Then P(Norman_late = true) = 1
    - This is an example of hard evidence



Soft evidence

◊ One day we look into Norman's office he is not there

Soft evidence – 2

- One day we look into Norman's office he is not there
  - **We are not certain he is late**

Soft evidence – 3

- One day we look into Norman's office he is not there
  - **We are not certain he is late**
    - **He may have stepped out for a coffee**

Soft evidence – 4

- One day we look into Norman's office he is not there
  - **We are not certain he is late**
    - **He may have stepped out for a coffee**
    - **This is rare**

Soft evidence – 5

- One day we look into Norman's office he is not there
  - **We are not certain he is late**
    - **He may have stepped out for a coffee**
    - **This rare**
      - **We cannot say P(Norman_late = true) = 1**
      - **But it might be 0.9**

Soft evidence – 6

- One day we look into Norman’s office he is not there
  - **We are not certain he is late**
    - **He may have stepped out for a coffee**
    - **This rare**
      - **We cannot say P(Norman_late = true) = 1**
      - **But it might be 0.9**
- This kind of evidence is called soft evidence

Soft evidence – 7

- One day we look into Norman's office he is not there
  - **We are not certain he is late**
    - **He may have stepped out for a coffee**
    - **This rare**
      - **We cannot say P(Norman_late = true) = 1**
      - **But it might be 0.9**
- This kind of evidence is called soft evidence
  - **Most commonly, it is taken to mean that P(Norman_late) is (0.9, 0.1)**

Soft evidence – 8

- One day we look into Norman's office he is not there
  - **We are not certain he is late**
    - **He may have stepped out for a coffee**
    - **This rare**
      - **We cannot say P(Norman_late = true) = 1**
      - **But it might be 0.9**
- This kind of evidence is called soft evidence
  - **Most commonly, it is taken to mean that P(Norman_late) is (0.9, 0.1)**
    - **This is propagated throughout the model**

Soft evidence – 9

- One day we look into Norman's office he is not there
  - We are not certain he is late
    - He may have stepped out for a coffee
    - This rare
      - We cannot say P(Norman_late = true) = 1
      - But it might be 0.9
- This kind of evidence is called soft evidence
  - Most commonly, it is taken to mean that P(Norman_late) is (0.9, 0.1)
    - This is propagated throughout the model
      - It is difficult to implement and many modeling programs take a different meaning for a simpler calculation

Soft evidence – 10

- The soft evidence eliminates the possibility to observe the NA state in this model