Artificial & Computational Intelligence

AIMLCZG557

M5 : Probabilistic Representation and Reasoning

Indumathi V

Guest Faculty

BITS -WILP

BITS Pilani

Pilani Campus

Course Plan

M1 Introduction to AI

M2 Problem Solving Agent using Search

M3 Game Playing

M4 Knowledge Representation using Logics

M5 Probabilistic Representation and Reasoning

M6 Reasoning over time

M7 Ethics in AI

Module 5:
Probabilistic Representation and Reasoning

A. Inference using full joint distribution

B. Bayesian Networks

I. Knowledge Representation

II. Conditional Independence

III. Exact Inference

IV. Introduction to Approximate Inference

Q

$P(jmab)$

↳ chain rule → $P(j|ma) * P(m|a) * P(a|b) * P(b)$

→ $P(j|a) * P(m|a) \cdot P(a|b)$

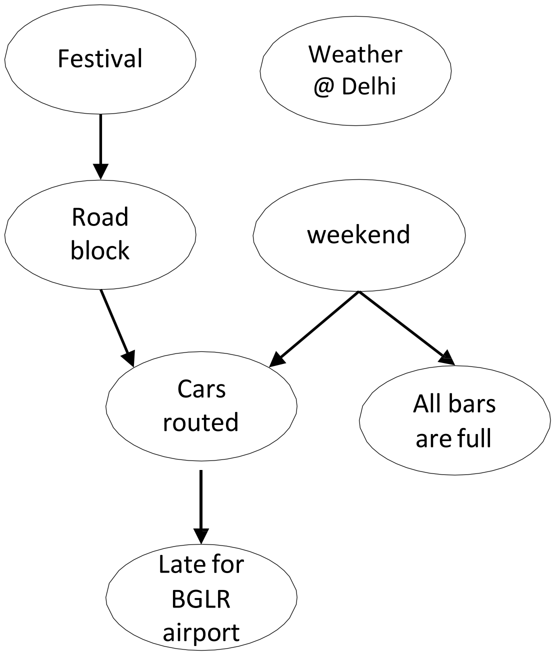
$P(jmab)$

$P($

Inferences in Bayesian Nets

Enumeration

Examples



$P(L \mid W \cap R \cap F \cap C)$

1. Calculate the probability that arrival at airport was delayed during a weekend but there was no road block or festival and car was not routed anywhere.

2. What is the probability that it is a festival season given cars where routed?

$P(F/C)$ condn prob

3. What is the probability that car arrived late at airport given it's a festival day?

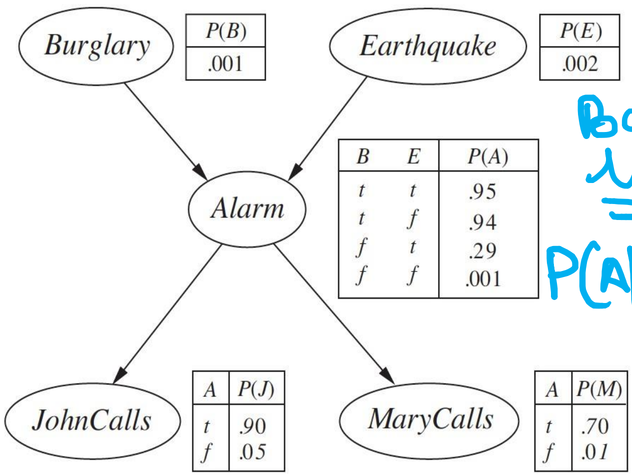
$P(L \mid F)$

Examples

Q: $P(B \mid JM) \rightarrow$ Joint prob distn $\rightarrow$ Linear $\rightarrow$ chain

2. What is the probability that Burglary happened given John & Mary called the police

$= P(A) + P(\neg A) = 1$



Bayes rule

$P(A \mid B) = \frac{P(A \cap B)}{P(B)} \Rightarrow \frac{P(AB)}{P(B)}$

$\rightarrow P(B \mid JM) + P(\neg B \mid JM) = 1$

$\frac{P(BJM)}{P(JM)} + \frac{P(\neg BJM)}{P(JM)} = 1$

$\frac{1}{P(JM)} \left[P(BJM) + P(\neg BJM) \right] = 1$

$P(JM) = P(BJM) + P(\neg BJM)$

let $\alpha = \frac{1}{P(JM)}$

$\alpha = \frac{1}{P(BJM) + P(\neg BJM)} \rightarrow 1$

$\boxed{P(B \mid J,M)} = \frac{P(B, J, M)}{P(J, M)}$

$P(B \mid J,M) = \frac{\sum_{A, E} P(J, M, A, B, E)}{\sum_{A, B, E} P(J, M, A, B, E)}$

$P(B \mid JM) \Rightarrow \frac{P(BJM)}{P(JM)} \Rightarrow \frac{P(AB)}{P(B)}$

$\Rightarrow \frac{P(BJM)}{P(BJM) + P(\neg BJM)} \rightarrow 1$

$P(BJM) \Rightarrow 0.5 \Rightarrow$

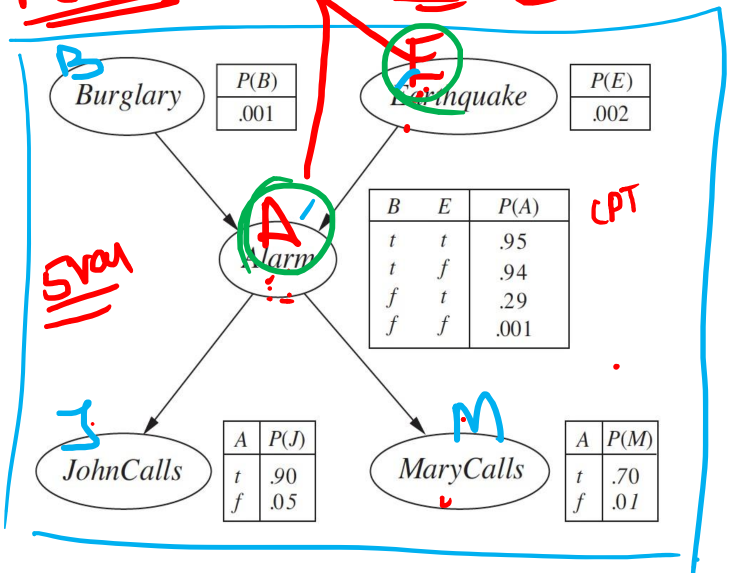
$P(\neg BJM) \Rightarrow 0.6$

~~Examples~~

$\frac{P(BJM)}{P(BJM)+P(\neg BJM)}$ $P(BJM) \Rightarrow$ 3 var $\Rightarrow$ $p(jm@b@)$

2. What is the probability that Burglary happened given John & Mary called the police

P(BJM) Hidden var



P(B)
.001

P(E)
.002

B	E	P(A)
t	t	.95
t	f	.94
f	t	.29
f	f	.001

A	P(J)
t	.90
f	.05

A	P(M)
t	.70
f	.01

$$P(B \mid J,M) = \frac{P(B, J, M)}{P(J, M)}$$

$$P(B \mid J,M) = \frac{\sum_{A, E} P(J, M, A, B, E)}{\sum_{A, B, E} P(J, M, A, B, E)}$$

$v_1 + v_2 + v_3 + v_4$ $P(BJM) \Rightarrow v_1+v_2+v_3+v_4 \Rightarrow$ Marginalization

addition Σ

$$P(B \mid JM) + P(\neg B \mid JM) = 1$$

$$\frac{P(BJM)}{P(JM)} + \frac{P(\neg BJM)}{P(JM)} = 1$$

$$\frac{1}{P(JM)}\left[P(BJM)+P(\neg BJM)\right] = 1$$

let $\alpha = \frac{1}{P(JM)}$

$$\alpha = \frac{1}{P(BJM)+P(\neg BJM)}$$

E	A	P(BJM)
T	T	— +
T	F	— +
F	T	— +
F	F	—

$\rightarrow$ 1

P(B)M

$$\boxed{P(B|JM)} = \sum_{A,E} P(J, M, A, B, E)$$

$$\sum_{A,E} P(J|\cancel{M}A\cancel{B}\cancel{E}) * P(M|A\cancel{B}\cancel{E}) * P(A|BE) * P(B|\cancel{E}) * P(E)$$

$$\sum_{A,E} P(J|A) * P(M|A) * P(A|BE) * P(B) * P(E)$$

E → T
¬E → F

A, E → remove / Expand the summation → 2 parts

A, ¬A

$$\sum_{A} P(J|A) * P(M|A) * P(A|BE) * P(B) * P(E) +$$
$$P(J|A) * P(M|A) * P(A|B\neg E) * P(B) * P(\neg E) \rightarrow A\ \neg A$$

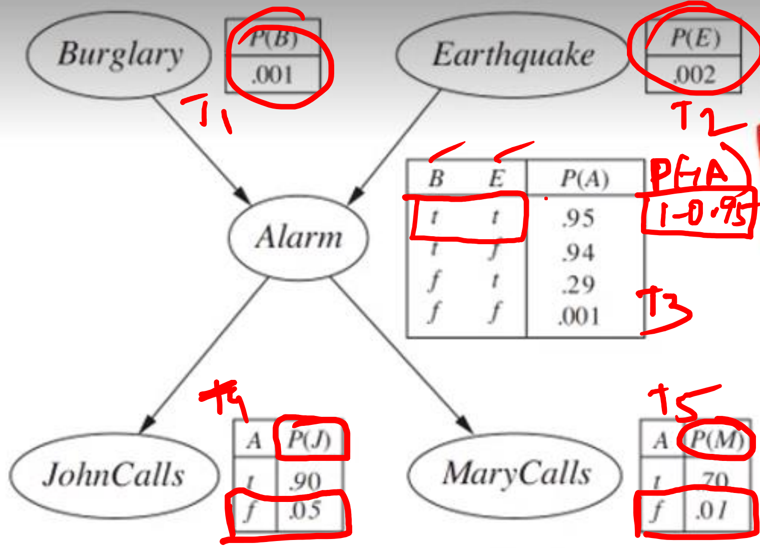
4

$v_1 \quad v_2 \quad v_3,\ \neg B \quad v_4 \quad v_4$

$$P(J|A) * P(M|A) * P(A|BE) * P(B) * P(E) + \Rightarrow V_1 +$$
$$P(J|\neg A) * P(M|\neg A) * P(\neg A|BE) * P(B) * P(E) + \Rightarrow V_2 +$$
$$P(J|A) * P(M|A) * P(A|B\neg E) * P(B) * P(\neg E) + V_3 +$$
$$P(J|\neg A) * P(M|\neg A) * P(\neg A|B\neg E) * P(B) * P(\neg E)\ V_4$$

$P(\neg B J M)$ ⓑ ← $P(BJM) = V$

$$P(B|JM) = \frac{P(BJM)}{P(BJM) + P(\neg BJM)}$$



2. What is the probability that Burglary happened given John & Mary called the police

$$P(B \mid J,M) = \frac{P(B, J, M)}{P(J, M)}$$

$$P(B \mid J,M) = \frac{\sum_{A, E} P(J, M, A, B, E)}{\sum_{A, B, E} P(J, M, A, B, E)}$$

$$\boxed{P(BJM)} = \sum_{A,E} P(J, M, A, B, E)$$

HV HV

chain rule

$$= \sum_{AE} P(J \mid MABE) \cdot P(M \mid ABE) \cdot P(A \mid BE) \cdot P(B \mid E) \cdot P(E)$$

$$= \sum_{AE} P(J \mid A) \cdot P(M \mid A) \cdot P(A \mid BE) \cdot P(B) \cdot P(E)$$

$$= \sum_A \sum_E P(J \mid A) \cdot P(M \mid A) \cdot P(A \mid BE) \cdot P(B) \cdot P(E)$$

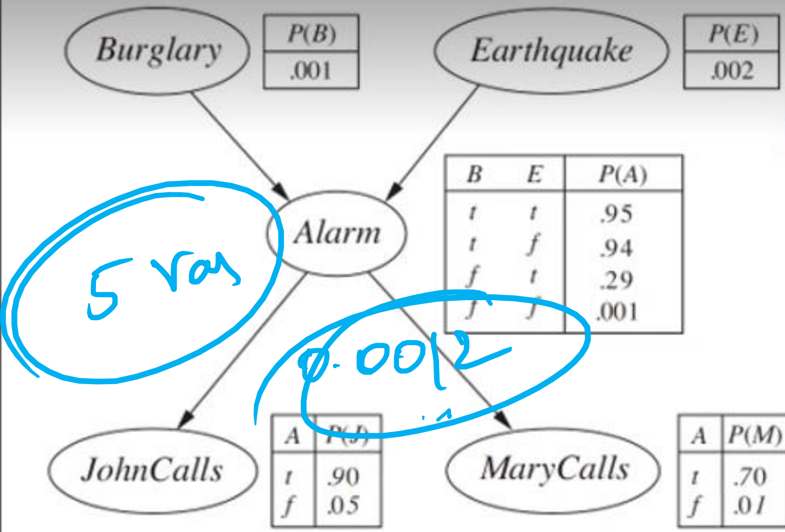
$$= \sum_A \{P(J \mid A) \cdot P(M \mid A) \cdot P(A \mid BE) \cdot P(B) \cdot P(E)\} + \{P(J \mid A) \cdot P(M \mid A) \cdot P(A \mid B\neg E) \cdot P(B) \cdot P(\neg E)\}$$

$P(BJM) \Rightarrow P(\neg BJM)$

1 2 3 4

$$= [P(J \mid A) \cdot P(M \mid A) \cdot P(A \mid BE) \cdot P(B) \cdot P(E)] + [P(J \mid A) \cdot P(M \mid A) \cdot P(A \mid B\neg E) \cdot P(B) \cdot P(\neg E)]$$
$$+ [P(J \mid \neg A) \cdot P(M \mid \neg A) \cdot \boxed{P(\neg A \mid BE)} \cdot P(B) \cdot P(E)] + [P(J \mid \neg A) \cdot P(M \mid \neg A) \cdot P(\neg A \mid B\neg E) \cdot P(B) \cdot P(\neg E)]$$

$0.05 * 0.01 * 0.05 * 0.001 * 0.002 \rightarrow \boxed{}$



2. What is the probability that Burglary happened given John & Mary called the police

$$P(B \mid J,M) = \frac{P(B, J, M)}{P(J, M)}$$

$$P(B \mid J,M) = \frac{\sum_{A,E} P(J, M, A, B, E)}{\sum_{A,B,E} P(J, M, A, B, E)}$$

$$\frac{P(BJM)}{P(BJM) + P(\neg BJM)}$$

$$\boxed{P(BJM)} = \sum_{A,E} P(J,M,A,B,E)$$

$$= \sum_{AE} P(J|MABE) \cdot P(M|ABE) \cdot P(A|BE) \cdot P(B|E) \cdot P(E)$$

$$= \sum_{AE} P(J|A) \cdot P(M|A) \cdot P(A|BE) \cdot P(B) \cdot P(E)$$

$$= \sum_{A}\sum_{E} P(J|A) \cdot P(M|A) \cdot P(A|BE) \cdot P(B) \cdot P(E)$$

$$= \sum_{A} \{P(J|A) \cdot P(M|A) \cdot P(A|BE) \cdot P(B) \cdot P(E) + P(J|A) \cdot P(M|A) \cdot P(A|B\neg E) \cdot P(B) \cdot P(\neg E)\}$$

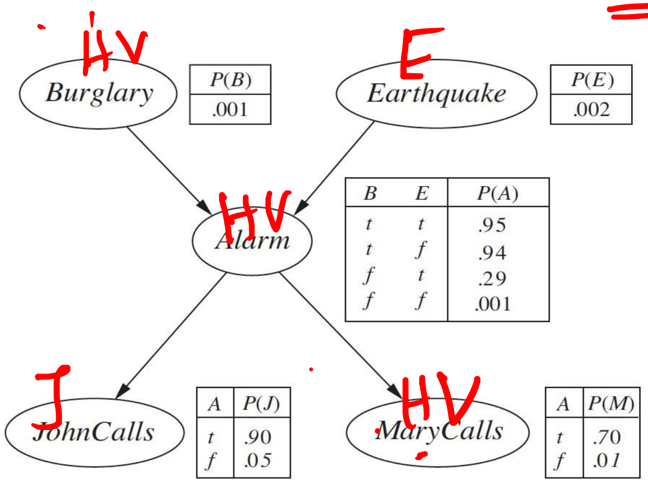
$$= [P(J|A) \cdot P(M|A) \cdot P(A|BE) \cdot P(B) \cdot P(E)] + [P(J|A) \cdot P(M|A) \cdot P(A|B\neg E) \cdot P(B) \cdot P(\neg E)]$$
$$+ [P(J|\neg A) \cdot P(M|\neg A) \cdot P(\neg A|BE) \cdot P(B) \cdot P(E)] + [P(J|\neg A) \cdot P(M|\neg A) \cdot P(\neg A|B\neg E) \cdot P(B) \cdot P(\neg E)]$$

Examples

H/W

$P(J|E) \Rightarrow$ Bayes rule $\Rightarrow \frac{P(JE)}{P(E)}$

3. What is the probability that John calls given earthquake occurred?



$$P(J \mid E) = \frac{P(J, E)}{P(E)}$$

$$P(J \mid E) = \frac{\sum_{M, A, B} P(J, M, A, B, E)}{\sum_{J, M, A, B} P(J, M, A, B, E)}$$

$$P(J|E) + P(\neg J|E) = 1$$

$$\frac{P(JE)}{P(E)} + \frac{P(\neg JE)}{P(E)} = 1$$

$$\frac{1}{P(E)}\left[P(JE) + P(\neg JE)\right] \Rightarrow 1$$

$$P(JE) + P(\neg JE) = P(E)$$

$$\frac{P(JE)}{P(JE) + P(\neg JE)}$$

$$\sum_{MAB} P(JMABE)$$

$$P(J|mab) \rightarrow P(J|a)$$

Inferences in Bayesian Nets

Variable Elimination

Reduce Guaranteed Independent nodes

D-Connectedness Vs D-Separation

5 steps

Alg

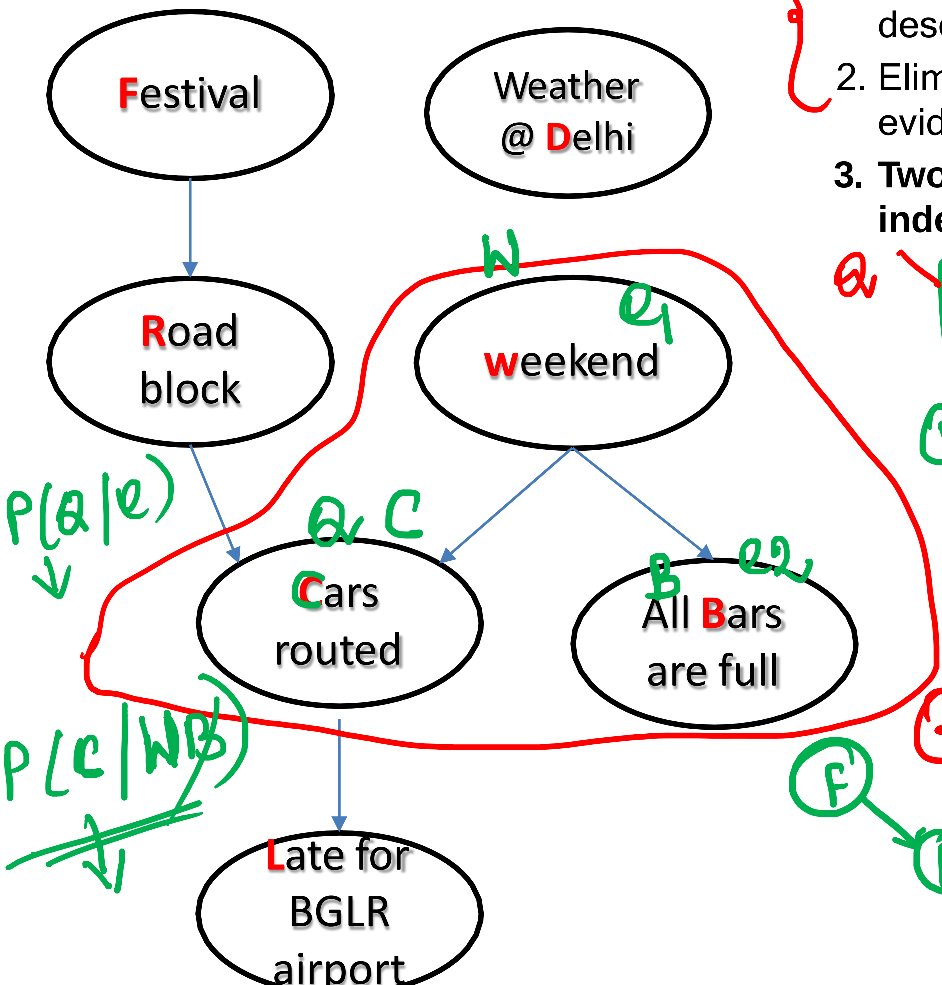
AI

I | a

1. Each variable is conditionally independent of its non-descendants, given its parents
2. Eliminate the hidden variables that is neither a query nor an evidence
3. **Two variables are d-separated if they are conditionally independent given evidences**

yes

e



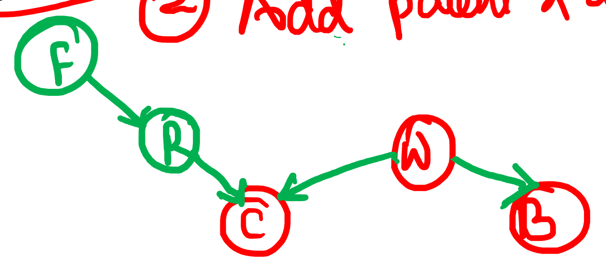
Q $\boxed{C \perp B \mid W}$ Prove?

① List all Q & E nodes

W

C B

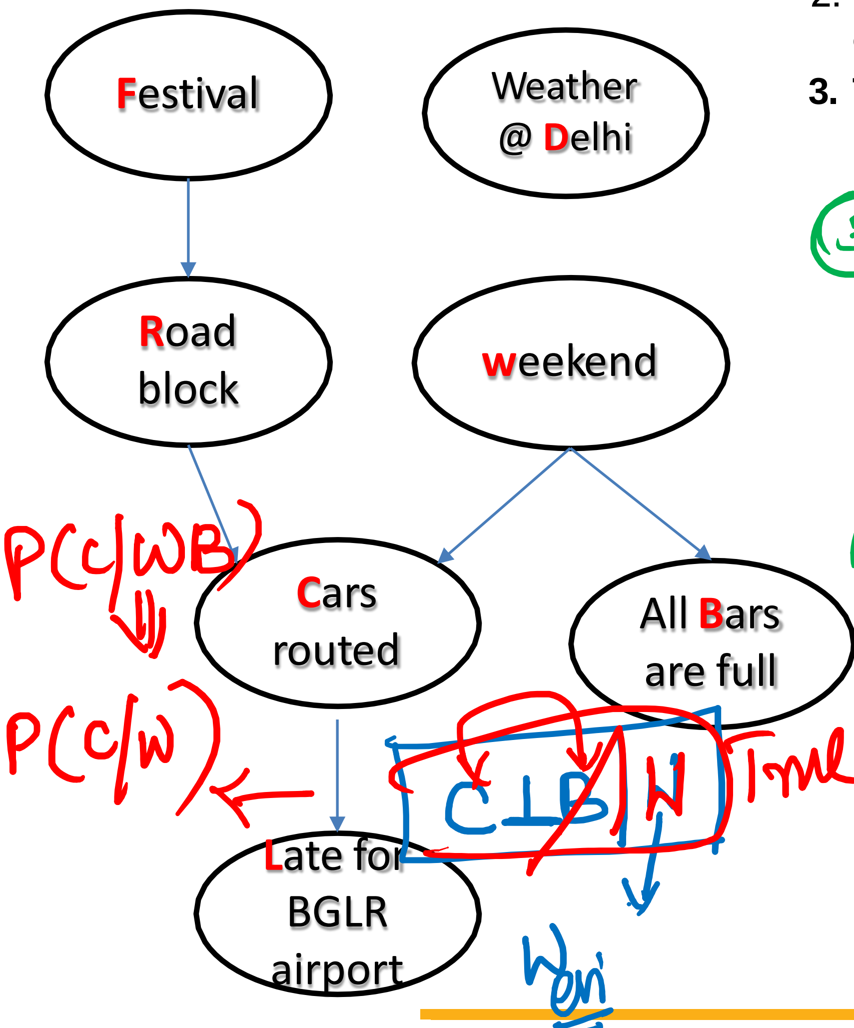
② Add parent & ancestors of Q & E nodes



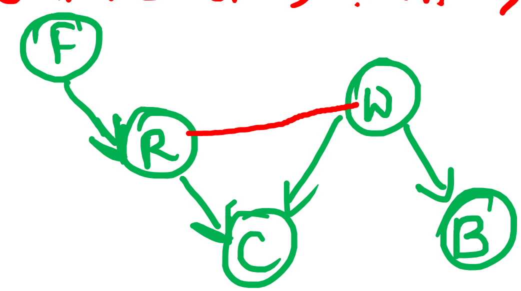
D-Connectedness Vs D-Separation

1. ~~Each variable is conditionally independent of its non-descendants, given its parents~~
2. Eliminate the hidden variables that is neither a query nor an evidence
3. **Two variables are d-separated if they are conditionally independent given evidences**

C - common child → R & W → Marrying.



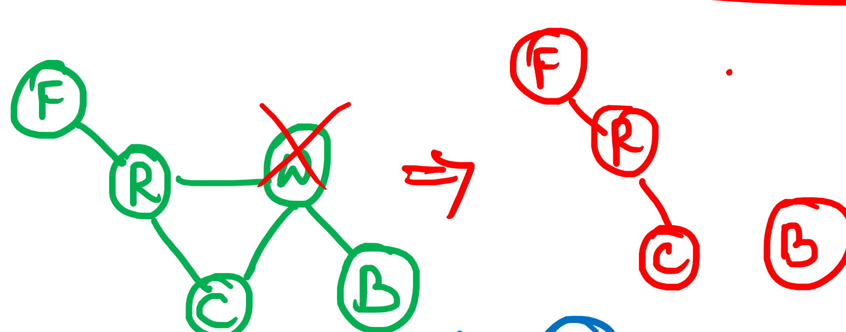
3



Yes

C & B are desepareted

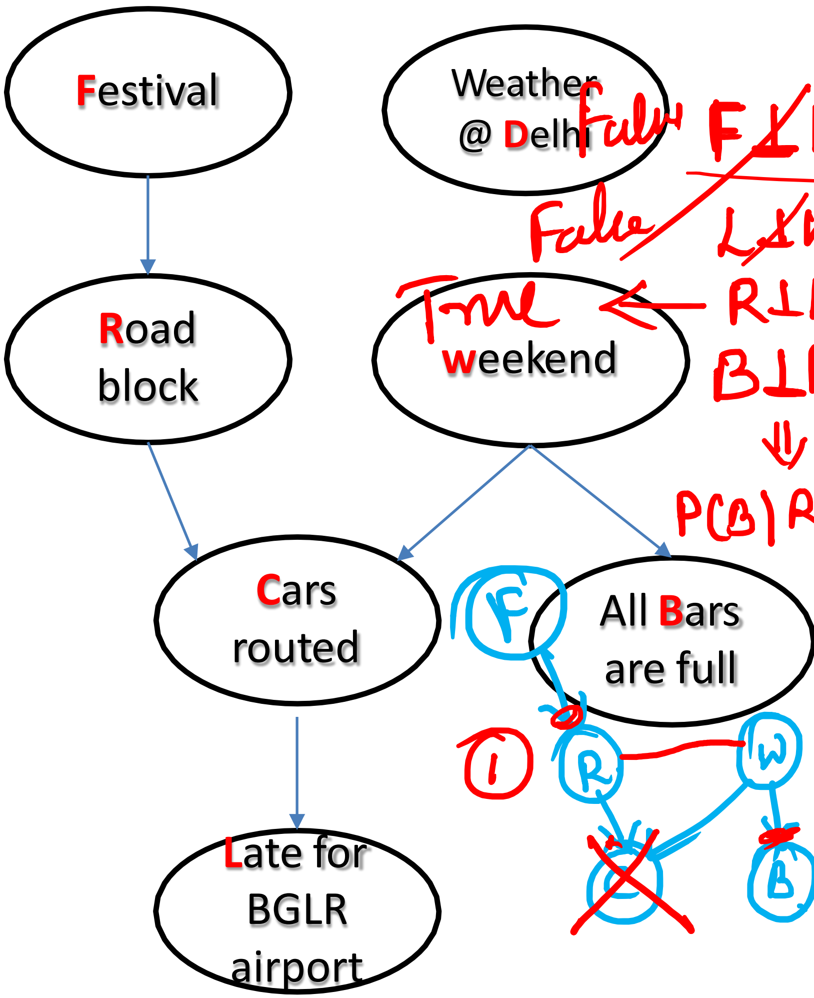
4



5 Remove evidence node W.

connection b/w C & B ⇒ NO

Try it & Test



False $F \not\perp W | C$

False $L \not\perp W | R$

True $R \perp L | C$

$B \perp R / C$

$\Downarrow$

$P(B | RC)$

$\Rightarrow$

Q AE E

X	Y	Evidence Z	d-sep?
F	W	C	No
L	W	R	No
R	**L**	**C**	**Yes**
B	R	C	No

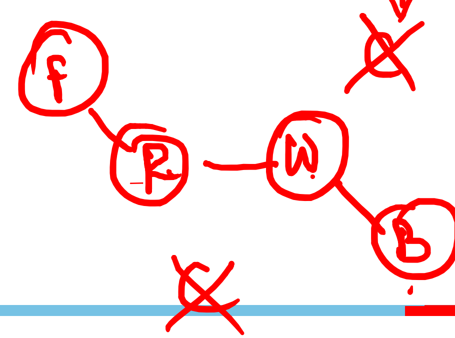
- P(R | L , C) = P(R| L)

$B \not\perp R | C$

R & L are d-separated ie., conditionally independent given C

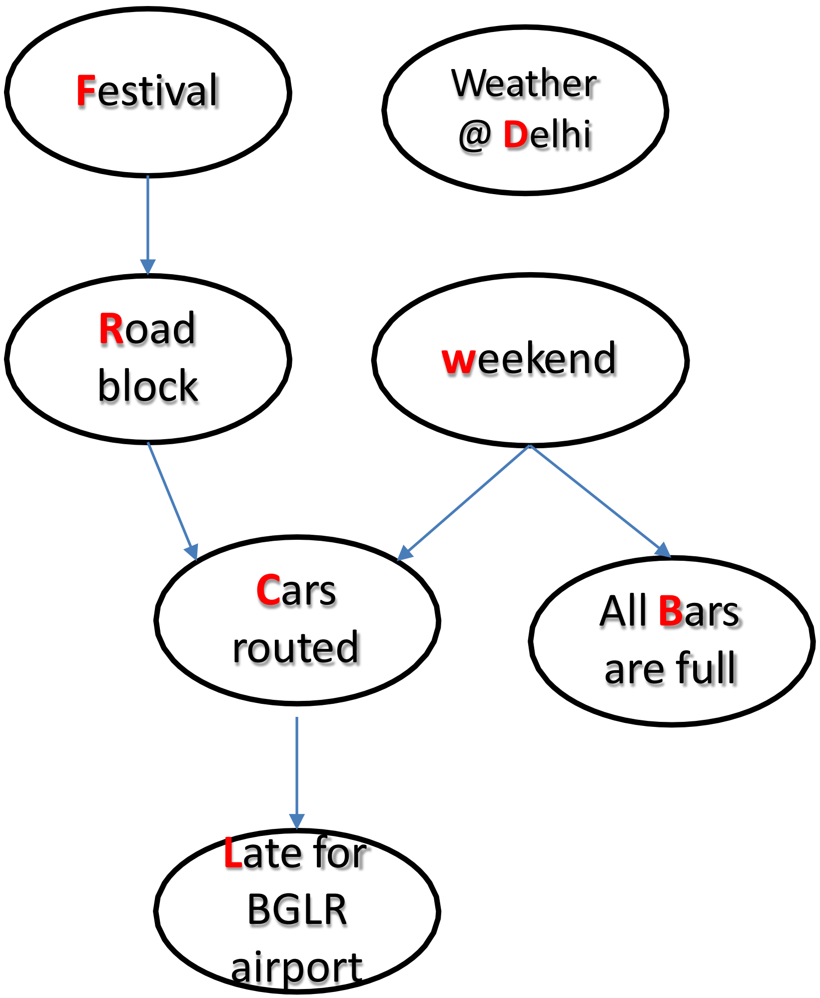
$B \perp R | C$

B & R are not deseperated



connect yes

Try it & Test

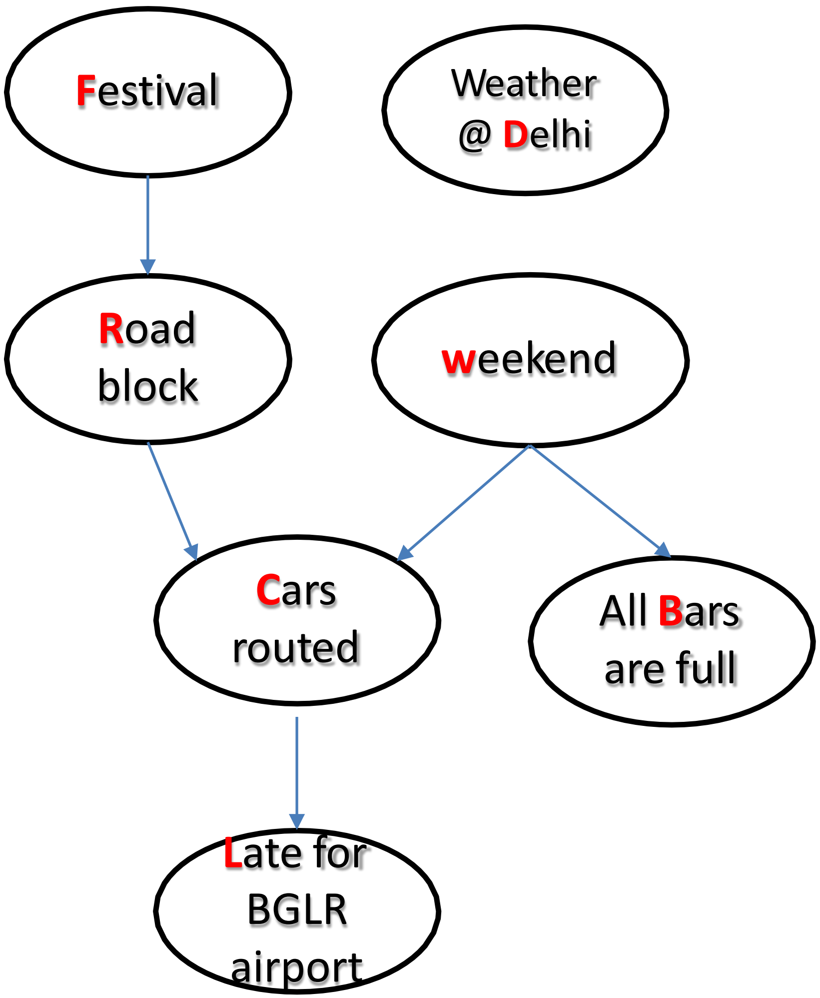


X	Y	Evidence Z	d-sep?
F	W	C	No
L	W	R	No
R	**L**	**C**	**Yes**
B	R	C	No

- P(R | L , C) = P(R| L)

R & L are d-separated ie., conditionally independent given C

Try it & Test



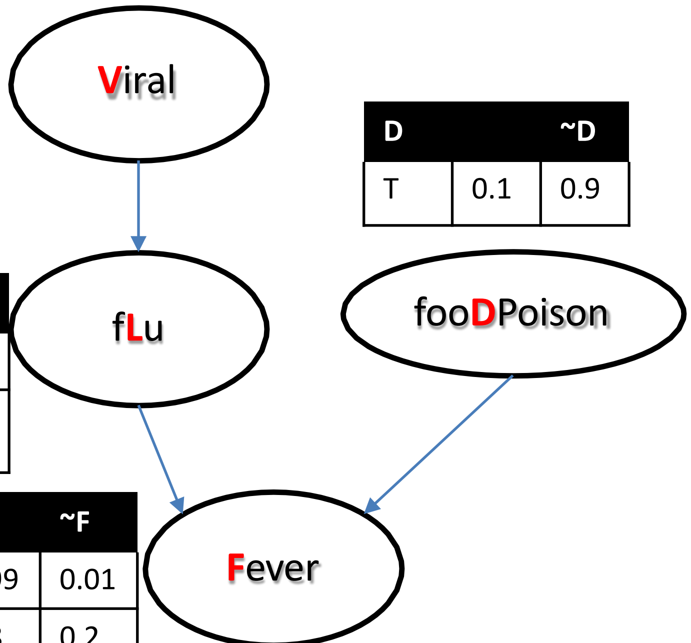
X	Y	Evidence Z	d-sep?
F	W	C	No
L	W	R	No
R	**L**	**C**	**Yes**
B	R	C	No

- P(R | L , C) = P(R| L)

R & L are d-separated ie., conditionally independent given C

D-Separation in Inference

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

X	Y	Evidence Z	d-sep?
V	F	L	Yes
V	D	L	Yes

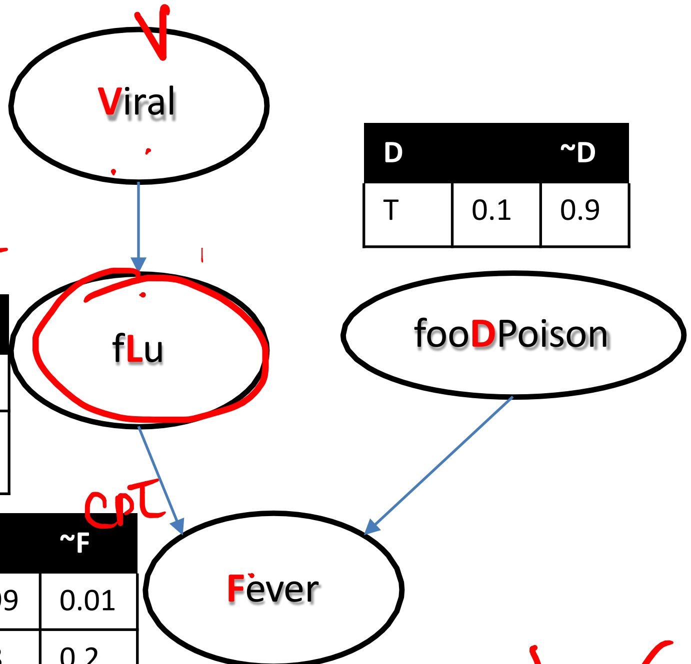
- $P(\overset{Q}{V} \mid \overset{e_1}{F}, \overset{e_2}{L}) \rightarrow V \perp F \mid L$
- $P(V \mid D, L)$

$V \perp D \mid L$

D-Separation in Inference

Enumeration

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

CPT

V	L	~L
T	0.8	0.2
F	0.01	0.99

CPT

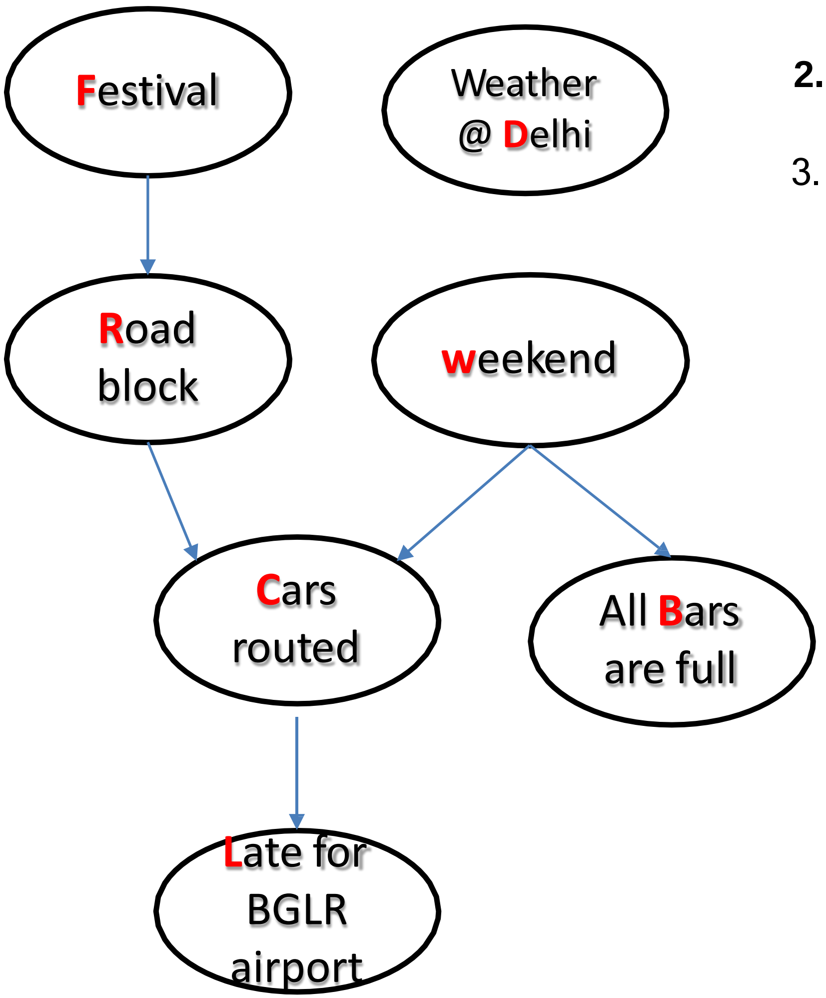
L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

P(V|F,L)

X	Y	Evidence Z	d-sep?
V	F	L	Yes
V	D	L	Yes

- P(V | F , L)
- P(V | D , L)

Variable Elimination



1. Each variable is conditionally independent of its non-descendants, given its parents
2. **Eliminate the hidden variables that is neither a query nor evidence**
3. Two variables are d-separated if they are conditionally independent given evidences

- $P(B) = \sum_{L, B, W, R, F} P(L, C, B, W, R, F)$
  $= \sum_{L} \sum_{B} P(L|C) \,.\, P(B \mid W) \,.\, \sum_{W} P(C \mid W, R) \,.\, \sum_{R} P(R \mid F) \,.\, \sum_{F} P(F)$
  $= \mathbf{P(B \mid W)}$

All other variables are hidden w.r.t to B as (L, C, R, F) are neither evidence nor query nor (L, C, R, F) $\in$ Ancestors(W, B)

This is variable elimination example targeting irrelevant nodes

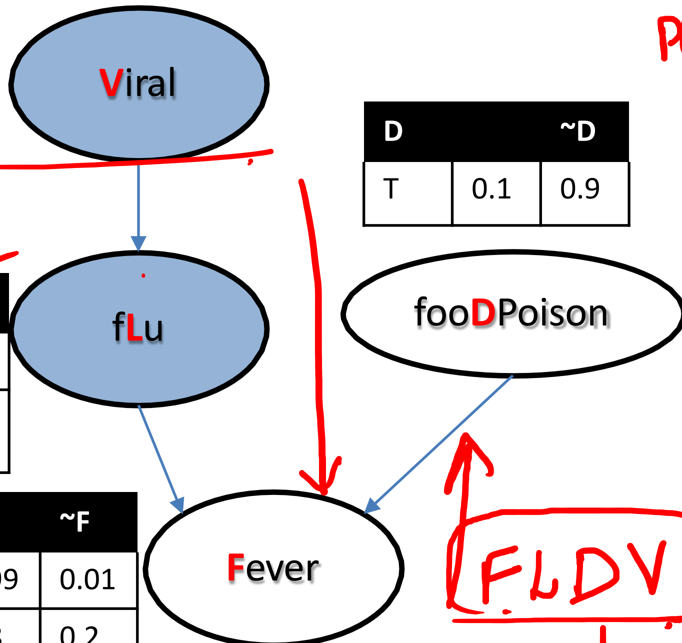
Inference

B N/W

T_1 Variable Elimination: V T_2

CPT

V		~V
T	0.6	0.4



T2

V	L	~L
T	0.8	0.2
F	0.01	0.99

D		~D
T	0.1	0.9

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

P(V)
P(L|V)
P(D)
P(F|L,D)

P(V)		P(~V)
T	0.6	0.4

V

V	P(L)	P(~L)
T	0.8	0.2
F	0.01	0.99

L

V	L	
T	T	0.48
T	F	0.12
F	T	0.004
F	F	0.396

P(

L	
T	0.484
F	0.516

FLDV

Reverse

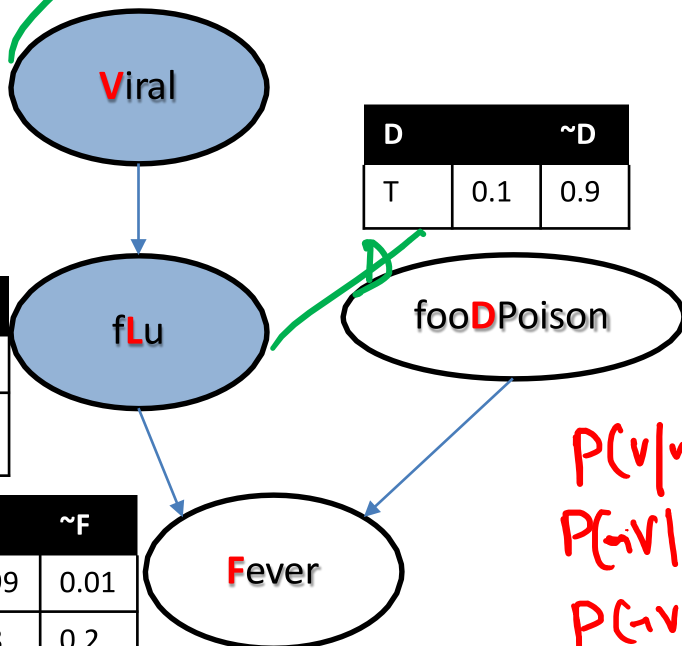
P(F) or P(~F)

v_1 v_2

V D L F

Marginalizing operation P(F)

Inference



V	~V	
T	0.6	0.4

V	L	~L
T	0.8	0.2
F	0.01	0.99

D	~D	
T	0.1	0.9

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

P(V)
P(L|V)
P(D)
P(F|L,D)

Variable Elimination: V (L)

T (V)

V	~V	
T	0.6	0.4

P(L)

V	L	~L
T	0.8	0.2
F	0.01	0.99

P(VL) → P(V|L).P(V)

V	L	
T	T	0.48
T	F	0.12
F	T	0.004
F	F	0.396

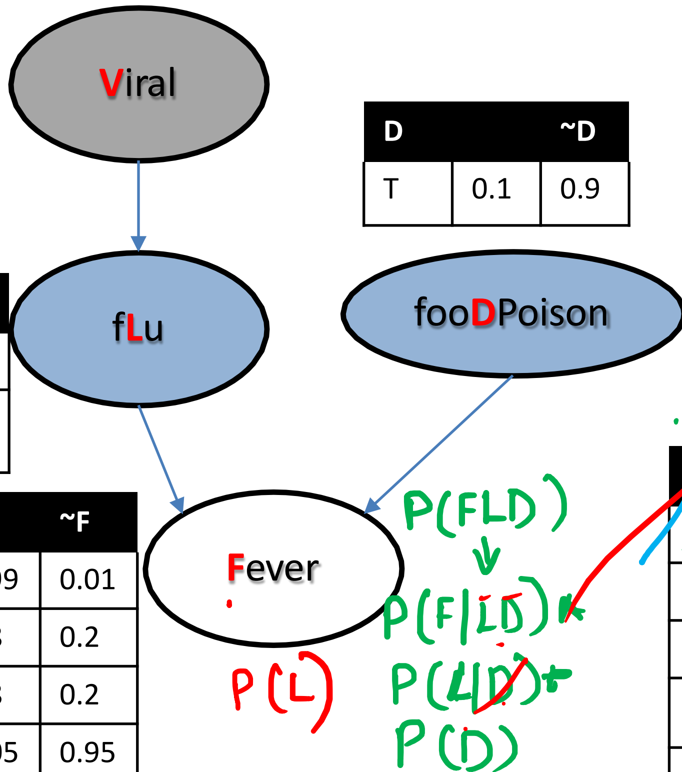
0.8 * 0.6
P(V|~L). P(V) → 0.2 * 0.6
P(~V|L).P(~V) → 0.01 * 0.4
P(~V|~L) . P(~V) → 0.99 * 0.4

L	
T	0.484
F	0.516

P(L) < T F

Inference

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

0.99*0.484*0.1

P(L)
P(D)
P(F|L,D)

Variable Elimination: L,D

T_1 L

L	
T	0.484
F	0.516

T_2 D

D		~D
T	0.1	0.9

T_3 F

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

2

[illegible]	L	F	
T	T	T	0.048
T	F	T	0.34852
F	T	T	0.04128
F	F	T	0.02322
T	T	F	0.00048
T	F	F	0.087
F	T	F	0.01032
F	F	F	0.44118

2var

L	F	
T	T	0.08928
F	T	0.37174
T	F	0.0108
F	F	0.52818

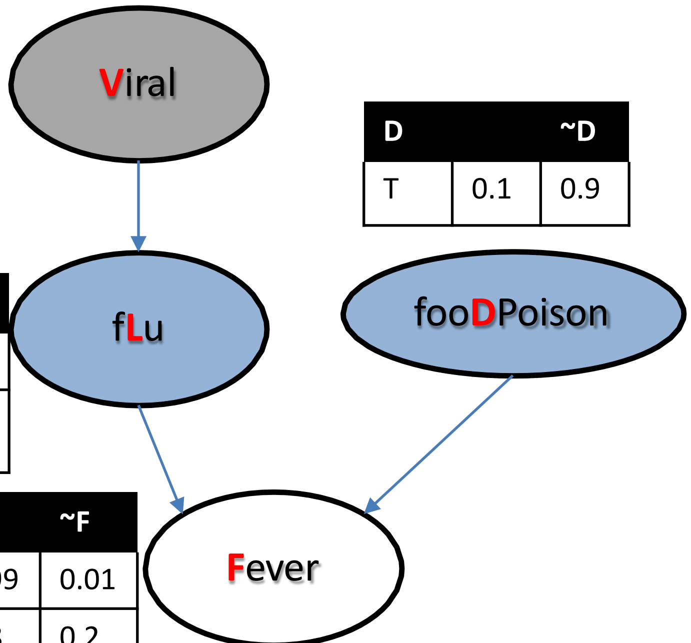
P(F)

F	
T	0.46102
F	0.53898

Inference

Variable Elimination: L

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

L	
T	0.484
F	0.516

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

P(L)
P(D)
P(F|L,D)

Approximate Inferences in Bayesian Nets

Introduction

Direct Sampling

↳ 3 → Prior samp

Rejection samp

Likelihood "

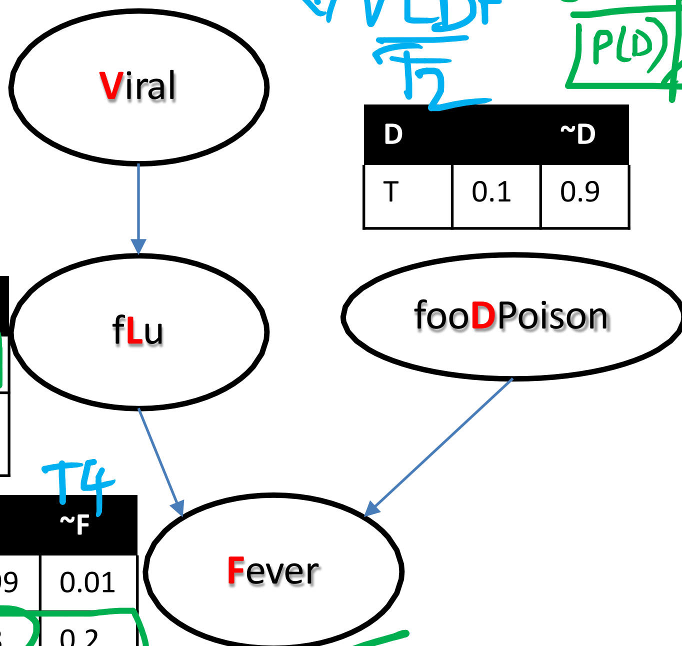
$P(V)\ P(\sim V) \Rightarrow P(\sim V)\ P(V)$

Prior Sampling

Sample Generation by Randomization

T1

V		~V
T	0.6	0.4



FDLV → VLDF

T2

D		~D
T	0.1	0.9

T3

V	L	~L
T	0.8	0.2
F	0.01	0.99

T4

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

0 0.1 1 P(D) P(~D) 0.6 F

V	L	D	F
T	T	F	T

6 bits

T P(V) P(~V) 0 0.3 0.6 1

0.2 → L T P(L) P(~L) 0 0.2 0.8 1

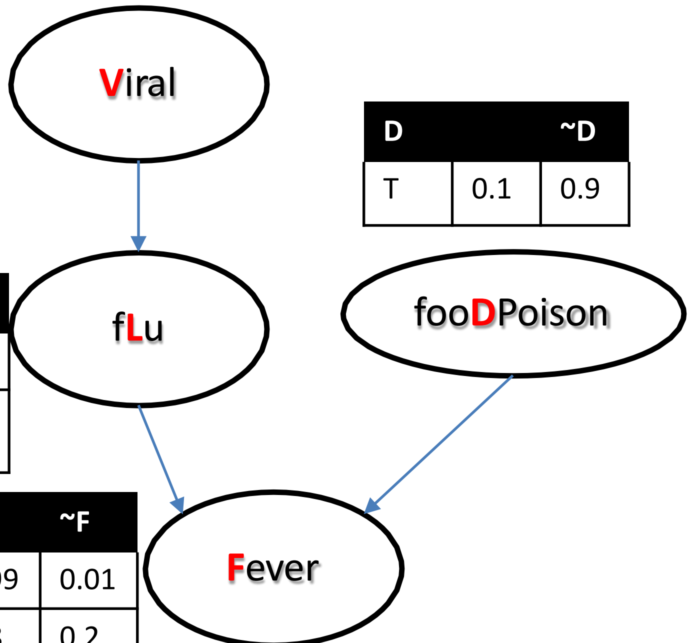
0.3, 0.2, 0.6, 0.58, 0.73, 0.87, 0.15, 0.6, 0.57, 0.85, 0.12, 0.004, 0.93 , 0.0002, 0.9, 0.55………….

generate 0.58

Prior Sampling

Sample Generation by Randomization

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

V	L	D	F
T	T	F	T
F	F	F	F
T	F	F	T
F	T	F	T
..			
…..			

0.3, 0.2, 0.6, 0.58, 0.73, 0.87, 0.15, 0.6, 0.57, 0.85, 0.12, 0.004, 0.93 , 0.0002, 0.9, 0.55………..

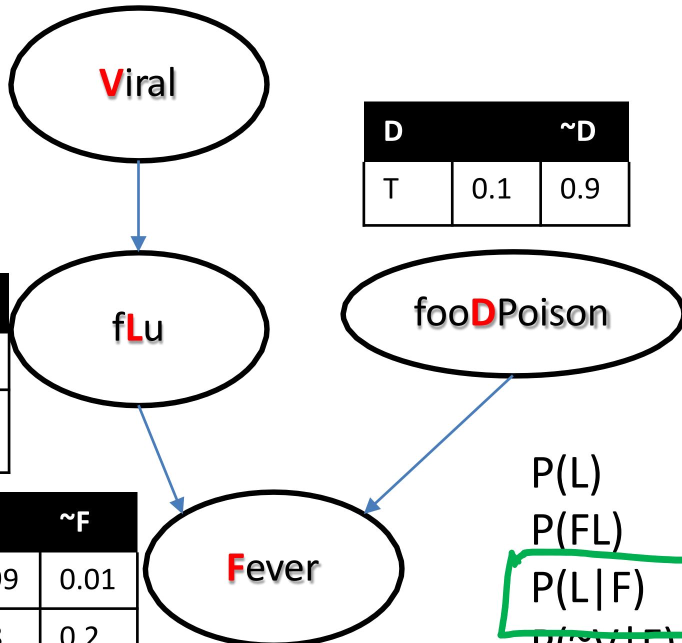
Prior Sampling

V		~V
T	0.6	0.4

D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95



Inference

Q E

V	L	D	F
T	T	F	T
F	F	F	F
T	F	F	T
F	T	F	T
T	T	F	T
T	F	F	F
F	F	F	T
T	F	F	F

8 insta

P(L) = 3/8
P(FL) = 3/8
$\boxed{P(L|F) = 3/5}$
P(~V|F) = 2/5
P(L|V~F) = 0
P(F|D) = ?????

Q ↓ LE

P(L|F) ⇒ # matches w.r.t Q / # matches w.r.t E

T

⇒ 3/5

P(F/D) = 5/0

Rejection Sampling

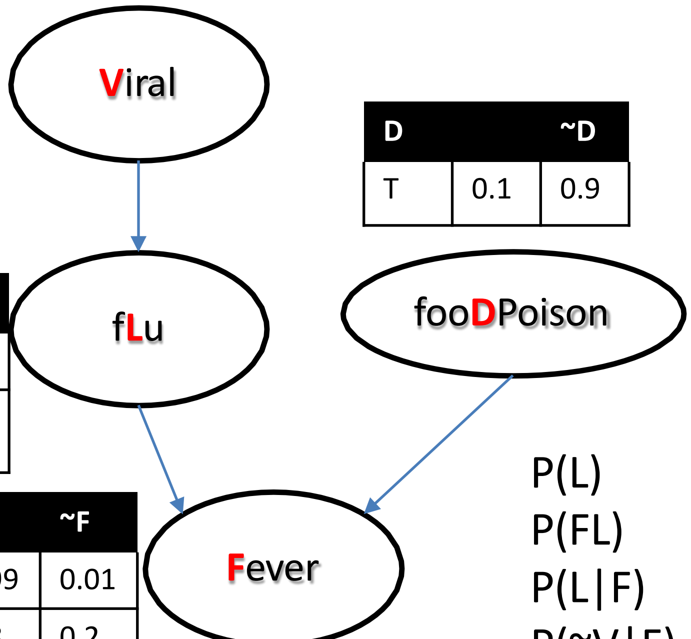
Sample Generation by Randomization

V		~V
T	0.6	0.4

D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95



V	L	D	F
T	T	F	
…..			

rejected

P(L) = 3/8
P(FL) = 3/8
P(L|F) = 3/5
P(~V|F) = 2/5
P(L|V~F) = 0
P(F|D) = ?????

D is true

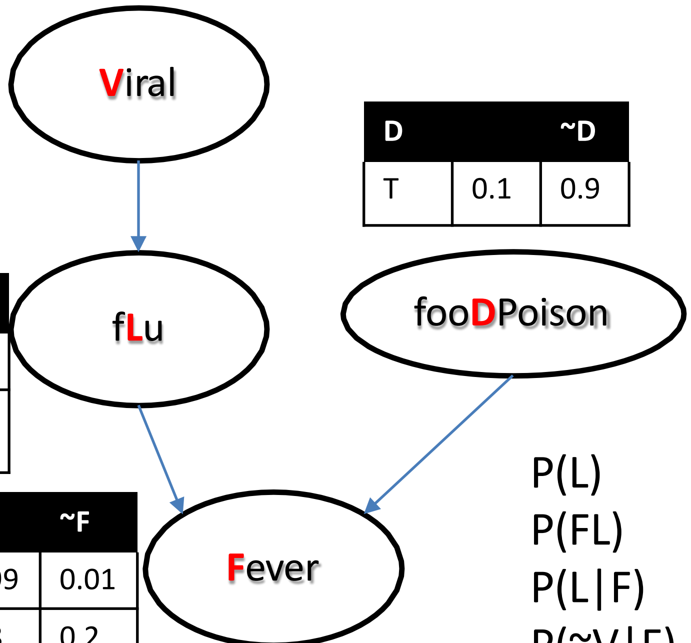
Q

0.3, 0.2, 0.6, 0.58, 0.73, 0.87, 0.15, 0.6, 0.57, 0.85, 0.12, 0.004, 0.93 , 0.0002, 0.9, 0.555, 0.38…………..

Rejection Sampling

Sample Generation by Randomization

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

D true

V	L	D	F
T	T	F	
T	T	F	
T	T	F	
F	F	T	F
T	F	T	T
…..			

Rejection
reje
rej

8 or

P(L) = 3/8
P(FL) = 3/8
P(L|F) = 3/5
P(~V|F) = 2/5
P(L|V~F) = 0
P(F|D) = ?????

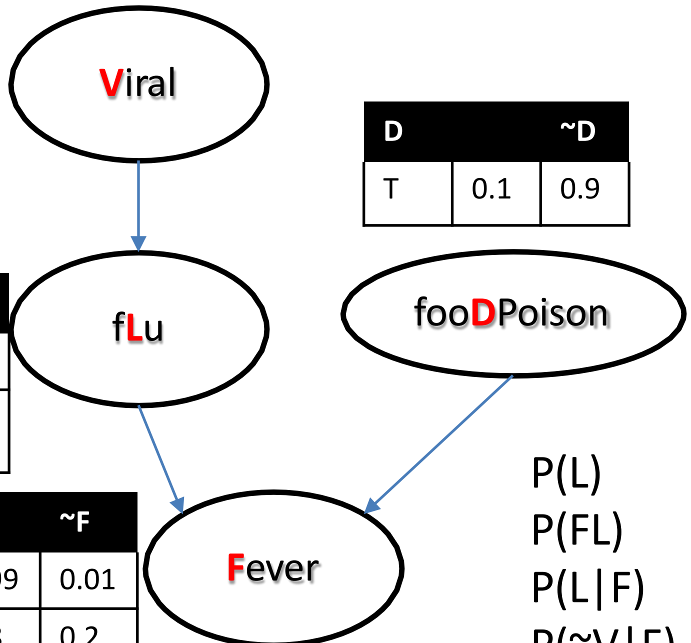
0.3, 0.2, 0.6, 0.58, 0.73, 0.87, 0.15, 0.6, 0.57, 0.85, 0.12, 0.004, 0.93, 0.0002, 0.9, 0.555, 0.38……….

V L D F

Rejection Sampling

Inference

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

D T

8

V	L	D	F
T	T	T	T
F	F	T	F
T	F	T	T
F	T	T	T
T	T	T	T
T	F	T	F
F	F	T	T
T	F	T	F

8

P(L) = 3/8
P(FL) = 3/8
P(L|F) = 3/5
P(~V|F) = 2/5
P(L|V~F) = 0
P(F|D) = 5/8

$$\frac{5}{8}$$

e_1 e_{98} e_1

$P(Q \mid e_1 e_2 \cdots e_{99} e_{100})$

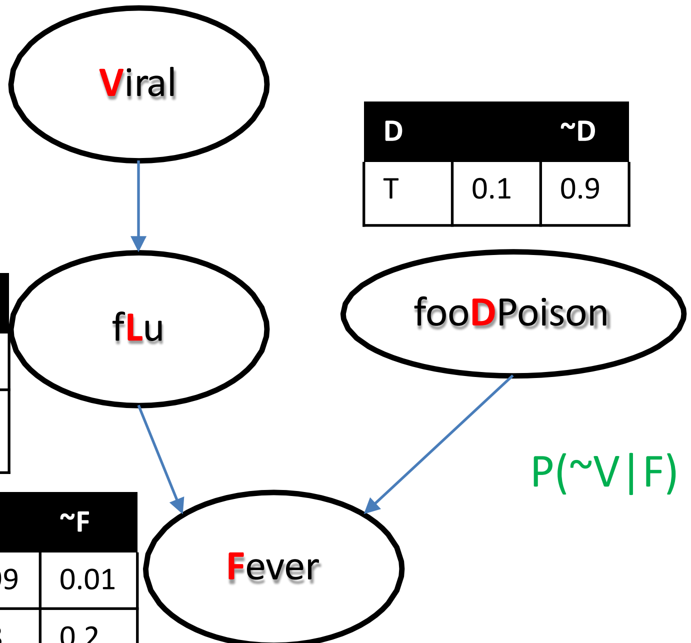
T T . . . .

rejected

Rejection Sampling

Sample Generation by Randomization

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

V	L	D	F
T	T	F	T
F	F	F	
T	F	F	T
F	T	F	T
…..			

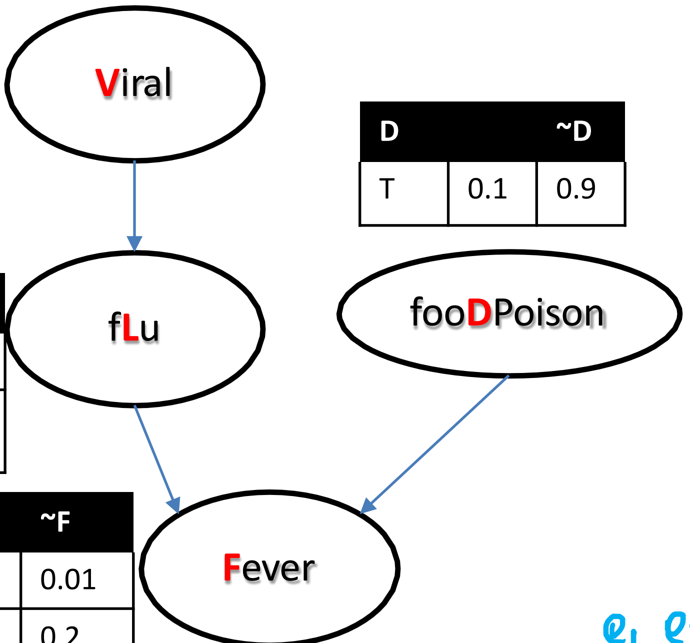
P(~V|F) = ?

0.3, 0.2, 0.6, 0.58, 0.73, 0.87, 0.15, 0.6, 0.57, 0.85, 0.12, 0.004, 0.93 , 0.0002, 0.9, 0.555, ………..

Likelihood Weighing

Sample Generation by Randomization

V	~V
T	0.6	0.4



D	~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

V	L	D	F	wgt
F		T		
F		T		
F		T		
F		T		
F		T		
F		T		
F		T		

e1 e2

$P(\sim F \mid D, \sim V) = 0.04 \;/\; 7 * 0.04$

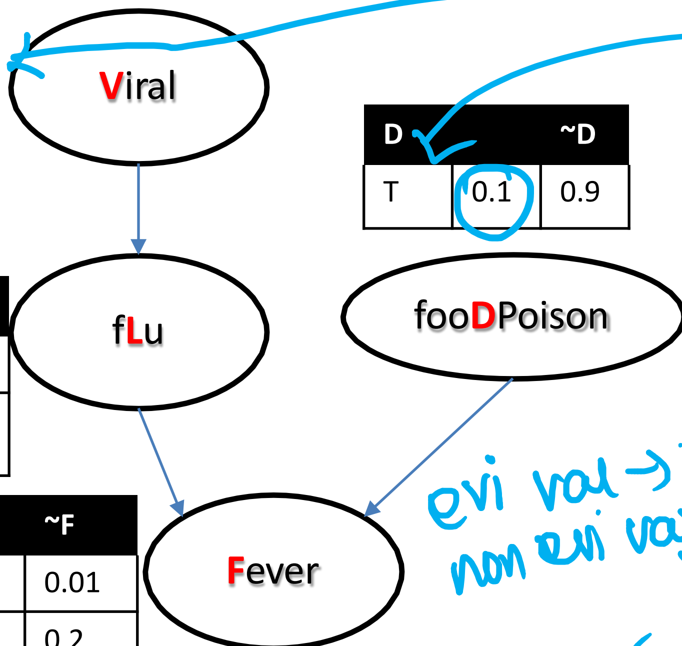
T F

0.3, 0.2, 0.58, 0.73, 0.87, 0.15, 0.6, 0.57, 0.85, 0.12, 0.004, 0.93 , 0.0002, 0.99, , ………..

Likelihood Weighing

P(~V)

	V	~V
T	0.6	0.4



	D	~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

Sample Generation by Randomization

V	L	D	F	wgt
F	F	T	T	0.4*1* 0.1 *1=
F	F	T	T	
F	F	T	T	
F	F	T	T	
F	F	T	T	
F	T	T	T	
F	T	T	F	

evi val → D V

non evi val → L F

→ wt ⇒ 1

P(~F|D,~V) = 0.04 / 7*0.04

0.3, 0.2, 0.58, 0.73, 0.87, 0.15, 0.6, 0.57, 0.85, 0.12, 0.004, 0.93 , 0.0002, 0.99, , ………..

F T F T F T F T T T T F

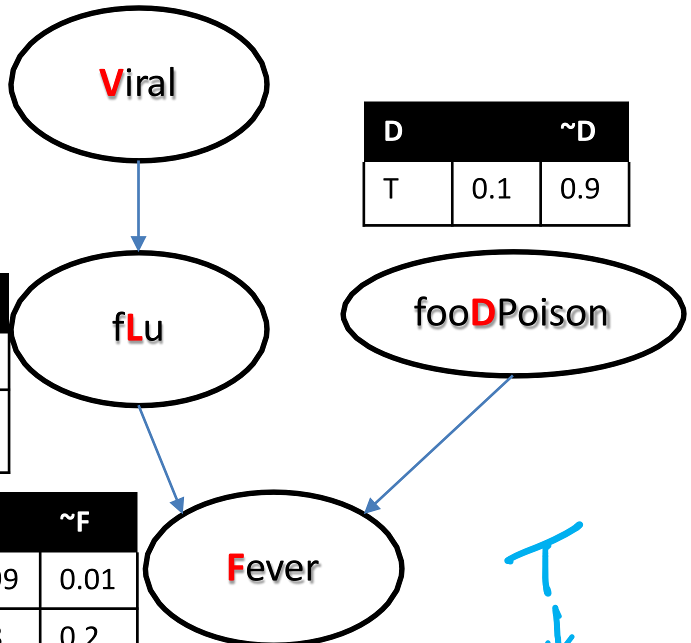
L F

F T

Likelihood Weighing

Inference

V	~V	
T	0.6	0.4



D	~D	
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

4 insts

V	L	D	F	wgt
F	F	T	F	0.4*1* 0.1 *1= 0.04
F	T	T	T	0.4*1* 0.1 *1= 0.04
F	F	T	T	0.4*1* 0.1 *1= 0.04
F	F	T	F	0.4*1* 0.1 *1= 0.04

$$\frac{\text{w.r.t } Q}{\text{w.r.t } E} = \frac{0.04+0.04}{4*0.04}$$

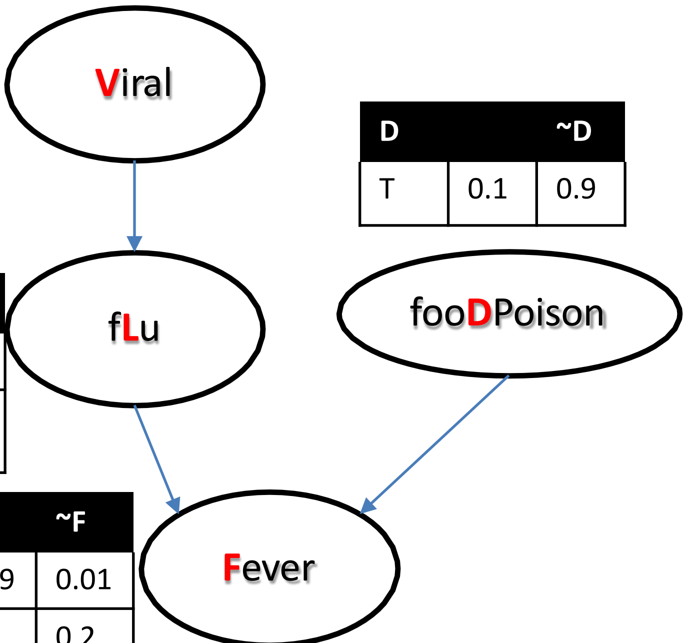
T

P(F|D,~V) = 0.04+0.04 / 4*0.04

T F

Likelihood Weighing

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

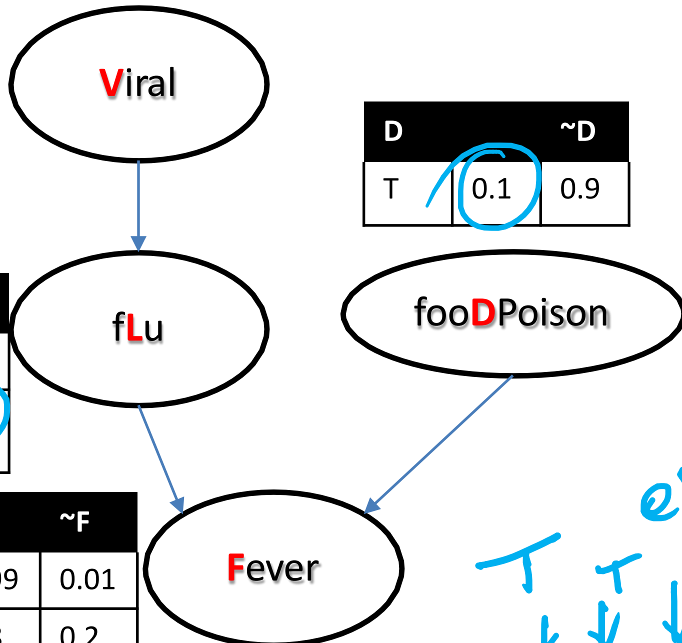
V	L	D	F	wgt
F	F	T	F	
F	F	T	T	
F	F	T	T	
T	F	T	F	

P(F|D,~L) = 0.099+0.099 / (3*0.099 + 0.02)

Likelihood Weighing

Inference

V		~V
T	0.6	0.4



D		~D
T	0.1	0.9

V	L	~L
T	0.8	0.2
F	0.01	0.99

L	D	F	~F
T	T	0.99	0.01
T	F	0.8	0.2
F	T	0.8	0.2
F	F	0.05	0.95

random

V	L	D	F	wgt
F	F	T	F	1*0.99* 0.1 *1=
F	F	T	T	1*0.99* 0.1 *1=
F	F	T	T	1*0.99* 0.1 *1=
T	F	T	F	1*0.2* 0.1 *1=

evidu.

T T F

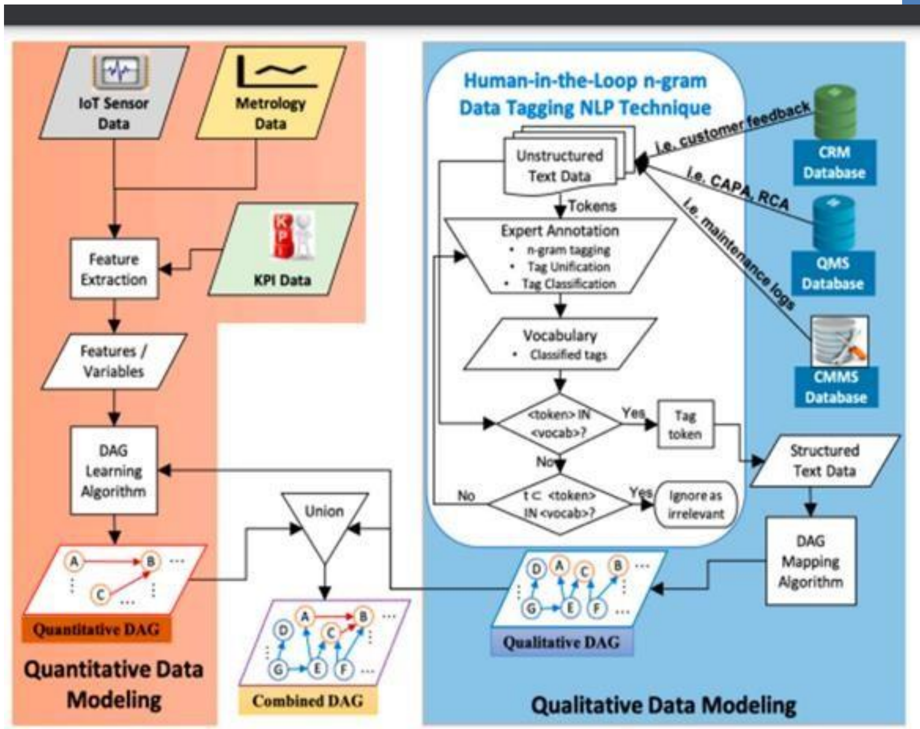
P(F | D,~L) = 0.099+0.099 / (3*0.099 + 0.02)

V L D F

1*0.99*0.1*1 ⇒

Bayesian Network

Fault Diagnostic System

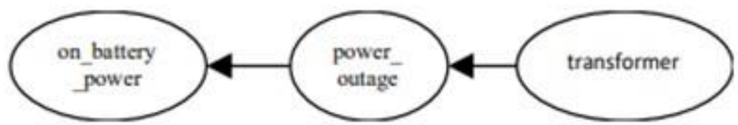


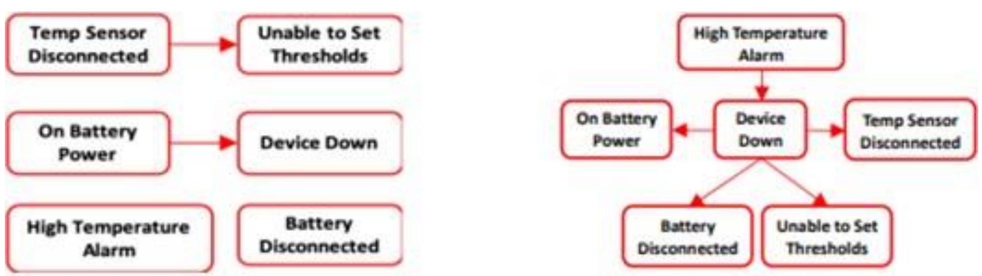
Source Credit : [Sensors 2021 : Fusion-Learning of Bayesian Network Models for Fault Diagnostics]

Bayesian Network

Fault Diagnostic System

Raw Data	Short Description		Resolution Notes			
	On battery power		Power outage due to transformer fire			
Classified Tags	Symptom		Cause(s)		Link	
	on_battery_power		power_outage, transformer_fire		due_to	
BN Mapping	Child Variable	Child State	Parent Variable	Parent State	Ancestor Variable	Ancestor State
	on_battery_power	yes	power_outage	yes	transformer	Fire





(a) (b)

Source Credit : [Sensors 2021 : Fusion-Learning of Bayesian Network Models for Fault Diagnostics]

Bayesian Network

Fault Diagnostic System

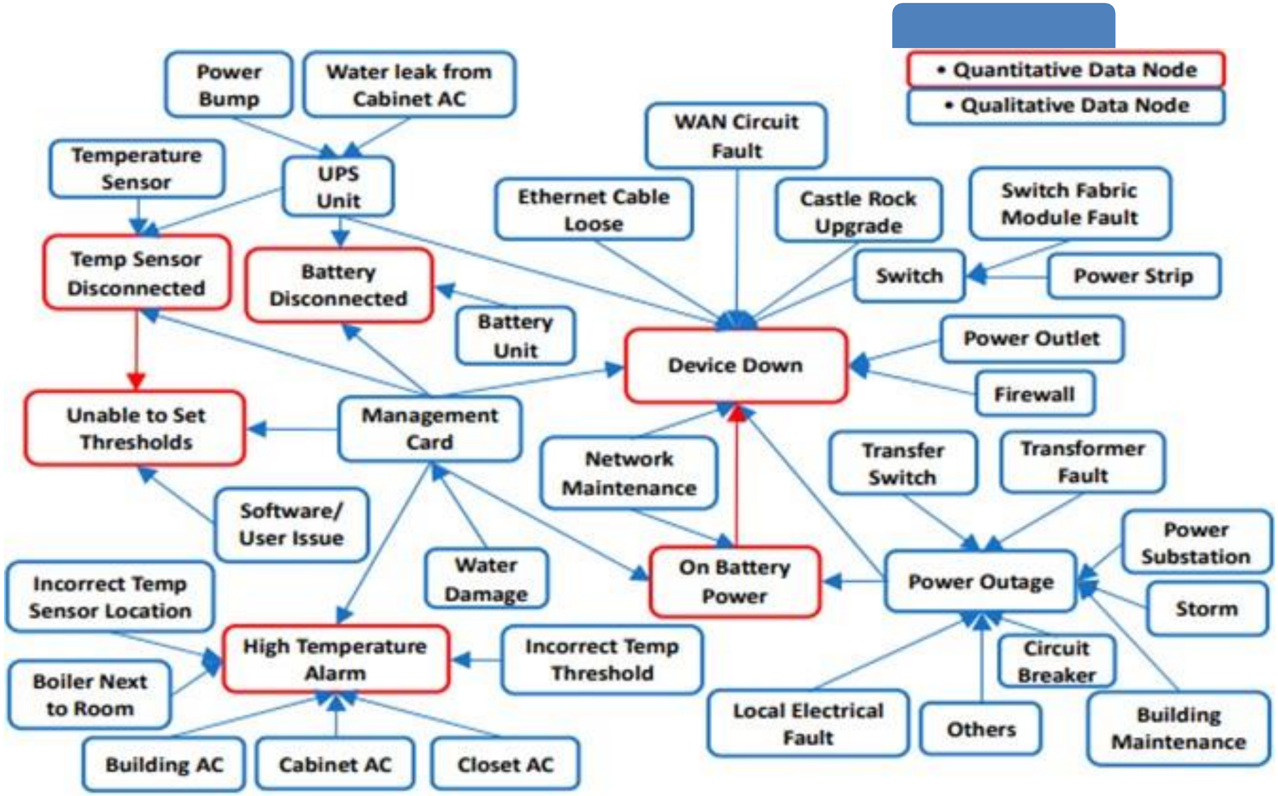
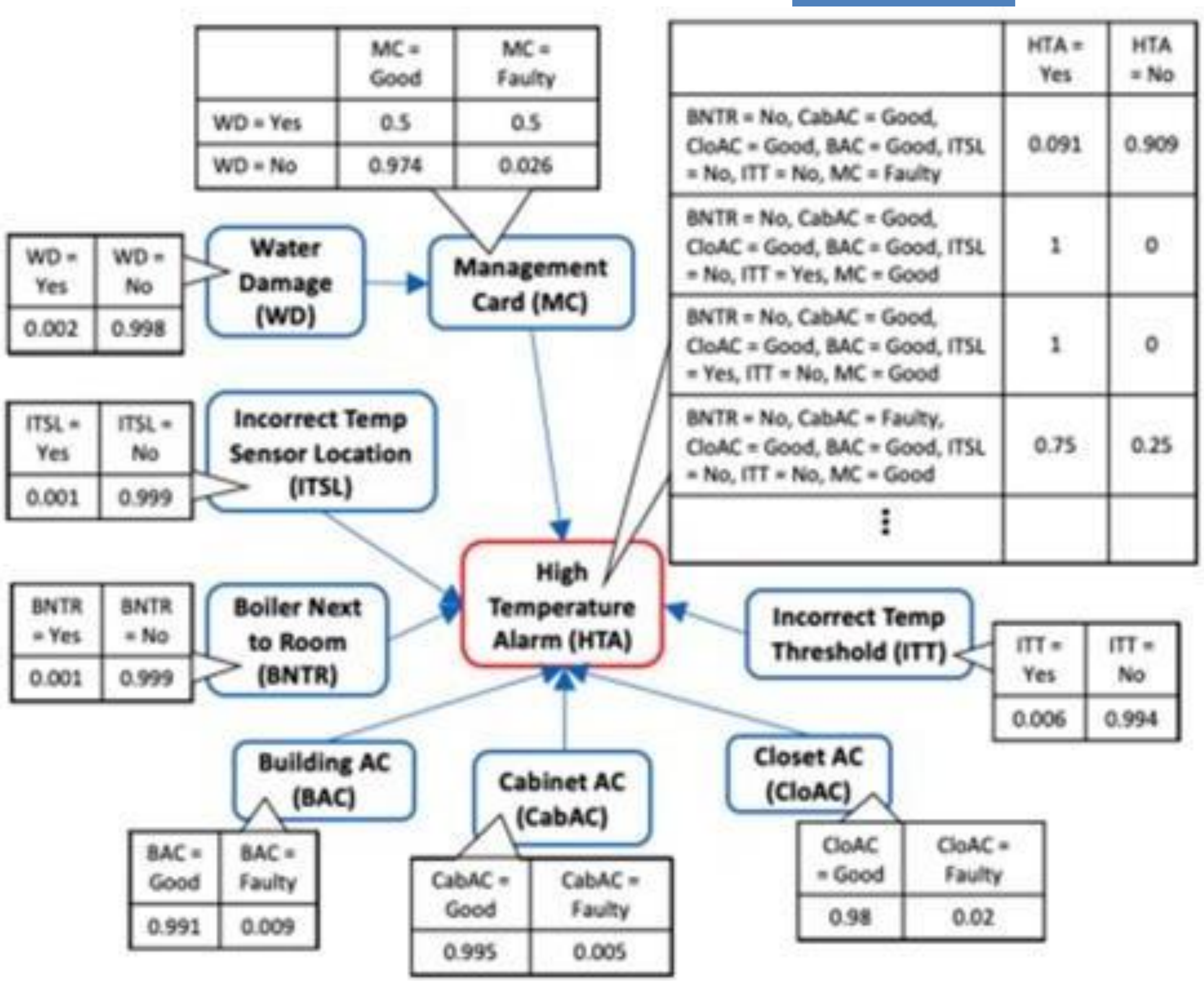


Figure 8. Fused Bayesian Network structure for top six occurring UPS messages.

Source Credit : [Sensors 2021 : Fusion-Learning of Bayesian Network Models for Fault Diagnostics]

Bayesian Network

Fault Diagnostic System



Source Credit : Sensors 2021 : Fusion-Learning of Bayesian Network Models for Fault Diagnostics

Required Reading: AIMA - Chapter # 4.1, #4.2, #5.1, #9 Refer to the handout

Next Session Plan:

- Hidden Markov Models

Thank You for all your Attention

Note : Some of the slides are adopted from AIMA TB materials