

Workshop 10

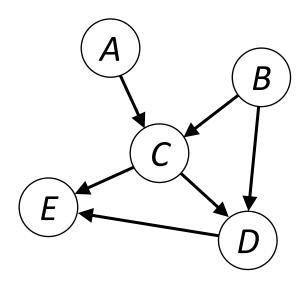
COMP90051 Machine Learning Semester 2, 2020

Learning Outcomes

By the end of this workshop you should be able to:

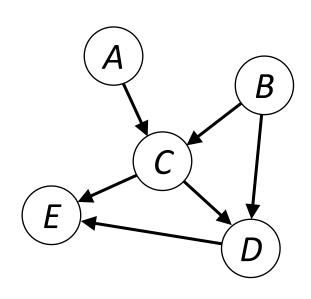
- write down the factorised joint distribution represented by a directed PGM
- answer probabilistic queries on simple directed PGMs by variable elimination
- 3. reason about independence between variables

- a) Find the factorised joint distribution
- b) Count the number of parameters in the CPTs

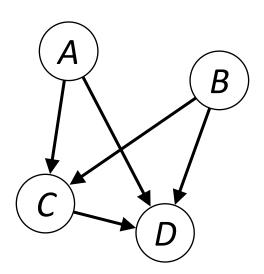


- a) Find the factorised joint distribution p(A, B, C, D, E) = p(E|C, D)p(D|C, B)p(C|A, B)p(A)p(B)
- b) Count the number of parameters in the CPTs

Node	# free params
Α	$2^0 = 1$
В	$2^0 = 1$
С	$2^2 = 4$
D	$2^2 = 4$
Ε	$2^2 = 4$
Total	14

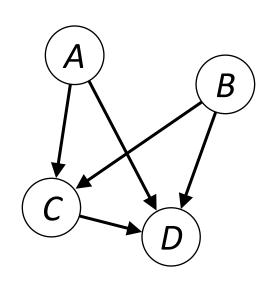


- a) Find the factorised joint distribution
- b) Count the number of parameters in the CPTs



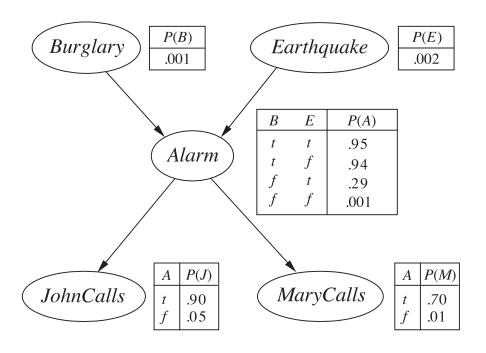
- a) Find the factorised joint distribution p(A,B,C,D) = p(D|A,B,C)p(C|A,B)p(A)p(B)
- b) Count the number of parameters in the CPTs

Node	# free params
Α	$2^0 = 1$
В	$2^0 = 1$
С	$2^2 = 4$
D	$2^3 = 8$
Total	14



Q2: Variable elimination

- Leo's house has an alarm to detect burglars
- The alarm is occasionally set off by an earthquake
- Leo's neighbours John and Mary (who don't know each other) sometimes call if they hear the alarm
- If Leo receives a call from John and Mary, what's the likelihood his house has been burgled?



Q2: Variable elimination

- Query analysis:
 - * Query nodes: Burglary
 - * Evidence (observed) nodes: *JohnCalls, MaryCalls*
 - * Latent (unobserved) nodes: Earthquake, Alarm
- Need to compute p(B|j,m)

Here lowercase means the observed value

Bayes' rule gives

$$p(B|j,m) = \frac{p(B,j,m)}{p(j,m)}$$

 Use the full joint distribution + marginalisation to compute the numerator and denominator

Q2: Variable elimination

Numerator:

$$p(B, j, m) = \sum_{E} \sum_{A} p(A, B, E, j, m) = p(B) \underbrace{\sum_{E} p(E) \sum_{A} p(A|B, E) \underbrace{p(j|A)p(m|A)}_{f_{j,m}(B,E)}}_{f_{j,m}(B,E)}$$

$$f_{j,m}(A) = \begin{cases} A & f_{j,m}(A) \\ 0 & 0.0005 \\ 1 & 0.63 \end{cases}$$

A	p(j A)
0	0.05
1	0.90

A	p(m A)
0	0.01
1	0.70

	В	E	$f_{j,m}(B,E)$
	0	0	0.0011295
$f_{j,m}(B,E) =$	0	1	0.183055
	1	0	0.59223
	1	1	0.598525

		p(A I)	B, E)
В	E	A=0	A=1
0	0	0.999	0.001
0	1	0.71	0.29
1	0	0.06	0.94
1	1	0.05	0.95

*

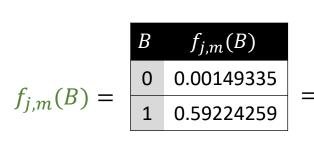
 $A f_{j,m}(A)$ 0 0.0005 1 0.63

Marginalising

over A

Marginalising

Q2: Variable elimination



	$f_{j,m}(B,E)$		
В	E=0	E=1	
0	0.0011295	0.183055	
1	0.59223	0.598525	

,		over	· E
	E	p(E)	
	0	0.998	
X	1	0.002	

	В	p(B)
co(D i cos) —	0	0.00149186
p(B,j,m) =	1	0.00059224

B	p(B)
0	0.999
1	0.001

В	$f_{j,m}(B)$
0	0.00149335
1	0.59224259

Denominator:

$$p(j,m) = \sum_{B} p(B,j,m) = 0.00149186 + 0.00059224 = 0.002084100239$$

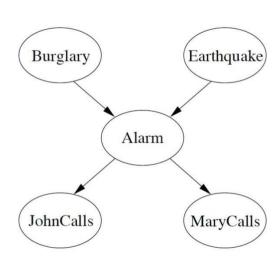
Putting the results together:

$$p(B=1|j,m) = \frac{p(B=1,j,m)}{p(j,m)} = \frac{0.00059224}{0.002084100239} = 0.28417184$$

Q3: Independence

Returning to the previous Bayes net:

- a) If no evidence is observed, are the Burglary and Earthquake nodes independent?
- b) What if we observe *Alarm* = t?
- c) Explain your answer to (b) intuitively.



Q3: Independence

Check for (marginal) independence:

$$p(B,E) = p(B)p(E) \sum_{A} p(A|B,E) \underbrace{\sum_{J} p(J|A)}_{=1} \underbrace{\sum_{M} p(M|A)}_{=1}$$
$$= n(B)p(E)$$

$$= p(B)p(E)$$

b) Check for (conditional) independence when we observe a = t:

$$p(B, E|a) \propto p(B)p(E)p(a|B, E) \underbrace{\sum_{J} p(J|a)}_{=1} \underbrace{\sum_{M} p(M|a)}_{=1}$$

$$\neq p(B|a)p(E|a)$$

Hint: see supplemental slides 'Independence in PGMs' for graphical rules

Q3: Independence

- c) Why are B and E dependent given a = t?
 - * The sub-graph consisting of B, E, A is known as a common effect structure (a.k.a. v-structure)
 - * Observing the effect (Alarm) puts the Burglar and Earthquake in competition as an explanation for the effect
 - * In other words, we expect B and E to be anticorrelated given a=t
 - * This is indeed the case—e.g. p(B=t|e=t,a=t)=0.003 and p(E=t|b=t,a=t)=0.002

