Probabilistic Reasoning Bayesian Networks

Conditional Probability, Product and Chain Rules

1) Definition of conditional probability:

$$P(a \mid b) = \frac{P(a,b)}{P(b)}, if P(b) \neq 0$$

NB:, means \wedge , so this is the same:

$$P(a \mid b) = \frac{P(a \land b)}{P(b)}, if P(b) \neq 0$$

The decomposition holds for any order of the variables

2) The *product rule* (follows from 1):

$$P(a,b) = P(a \mid b)P(b)$$

$$P(a,b) = P(b,a) = P(b \mid a)P(a)$$
 <- It works the other way too commutative property

3) *Chain rule* – derived by successive application of the product rule:

$$P(x_{1},...,x_{n}) = \prod_{i=1}^{n} P(x_{i} \mid x_{i-1},...,x_{1}), e.g.$$

$$P(a,b) = P(a \mid b)P(b)$$

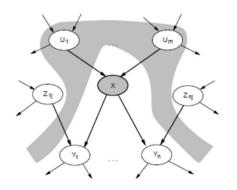
$$P(a,b,c) = P(a \mid b,c)P(b \mid c)P(c)$$

$$P(a,b,c,d) = P(a \mid b,c,d)P(b \mid c,d)P(c \mid d)P(d)$$

Assumption of Bayesian Networks (2)

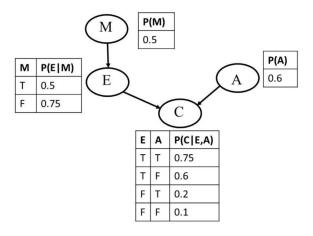
- Bayesian Network (BN) assumption: A node is conditionally independent of its *non-descendants*, given its parents
- In other words, if we know the values of the parents, then knowing the values of any other non-descendant does not change the probability values of the nodes
- This can be written as:

 $P(node \mid parents \ plus \ any \ other \ non-descendants) = P(node \mid parents)$



X is conditionally independent of its non-descendants (nodes Z_{ij}) given its parents (nodes U_i – the gray area)

Consider the Bayesian network below where all variables are binary:



Compute the following probability and show your calculations: P(M=T, E=T, A=F, C=T).

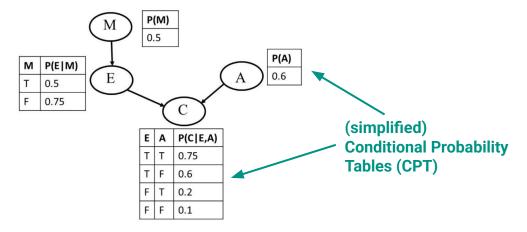
Bayesian Network Joint Probability Rule



Any joint probability can be computed as:

$$P(x_1,...,x_n) = \prod_{i=1}^n P(x_i \mid Parents(x_i))$$

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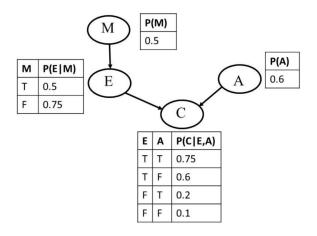
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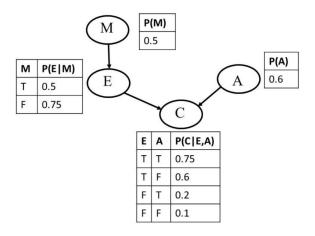
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Notation:

m denotes M=T
e denotes E=T
a denotes A=T => ~a denote A=F
c denotes C=T

Consider the Bayesian network below where all variables are binary:



• Any joint probability can be computed as:

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a denotes A=T => ~a denote A=F
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Compute the following probability and show your calculations: P(M=T, E=T, A=F, C=T).

Solution:

$$P(M=T, E=T, A=F, C=T) = P(m, e, \sim a, c) = P(m)P(e|m)P(\sim a)P(c|e, \sim a) = 0.5*0.5*(1-0.6)*0.6 = 0.06$$

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

	toothache		¬ toothache	
	catch	\neg catch	catch	\neg catch
cavity	.108	.012	.072	.008
¬ cavity	.016	.064	.144	.576

Calculate the following:

- a) P(toothache)
- b) $P(Cavity) \leftarrow$
- c) P(Toothache |cavity)
- d) $P(Cavity | toothache \lor catch) \stackrel{\checkmark}{\sim}$

Probability Distribution

• P(Meningitis)=<0.3, 0.7> the values should sum to 1 bold 1st value is for true, 2nd is for false

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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- a) P(toothache)
- b) **P**(Cavity)
- c) **P**(Toothache |cavity)
- d) $P(Cavity | toothache \lor catch)$

a) P(toothache)=P(Toothache=true)=0.108+0.012+0.016+0.064=0.2

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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Calculate the following:

- a) P(toothache)
- b) $P(Cavity) \leftarrow$
- d) **P**(Cavity| toothache ∨ catch) ✓

b) **P**(Cavity) = < P(Cavity=True), P(Cavity=False) >

Probability Distribution

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```
b) P(Cavity) = < P(Cavity=True), P(Cavity=False) > =< (0.108+0.012+0.072+0.008), (0.016+0.064+0.144+0.576) >=<0.2, 0.8>
```

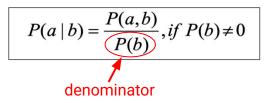
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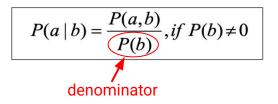


Two calculation methods:

- **Method 1: Without** α (i.e. by calculating the denominator)
- **Method 2: With \alpha** (i.e. without calculating the denominator)

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

	toothache		¬ too	thache
	catch	¬ catch	catch	¬ catch
cavity	.108	.012	.072	.008
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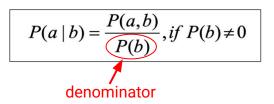


Method 1: Without α (i.e. by calculating the denominator)

P(toothache | cavity) = P(toothache, cavity)/P(cavity)

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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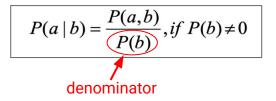


Method 1: Without α (i.e. by calculating the denominator)

P(toothache | cavity) = P(toothache, cavity)/P(cavity)
=
$$(0.108+0.012)/(0.108+0.012+0.072+0.008)$$
 = 0.12/0.2 = 0.6

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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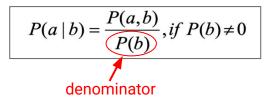
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= $0.12/0.2$ = 0.6

P(
$$\sim$$
toothache | cavity) = P(\sim toothache, cavity)/P(cavity)
= $(0.072+0.008)/(0.108+0.012+0.072+0.008)=0.08/0.2 = 0.4$

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

	toothache		¬ too	thache	
	catch	\neg catch	catch	¬ catch	
cavity	.108	.012	.072	.008	
¬ cavity	.016	.064	.144	.576	



Method 2: With \alpha (i.e. without calculating the denominator)

P(toothache | cavity) =
$$\alpha$$
 P(toothache, cavity)
P(\sim toothache | cavity) = α P(\sim toothache, cavity)

$$\alpha = 1/P(cavity)$$

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

	toothache		¬ toothache	
	catch	\neg catch	catch	\neg catch
cavity	.108	.012	.072	.008
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$$P(a \mid b) = \frac{P(a,b)}{P(b)}, if P(b) \neq 0$$
denominator

Method 2: With \alpha (i.e. without calculating the denominator)

P(toothache | cavity) =
$$\alpha$$
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P(~toothache | cavity) = α P(~toothache, cavity) = α (0.072 + 0.008) = α * 0.08

$$\alpha = 1/P(cavity)$$

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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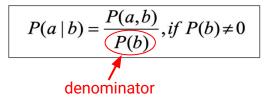
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$$\alpha = 1/P(cavity)$$

Next we calculate α - the normalisation term

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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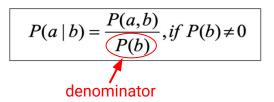
$$\alpha = 1/P(cavity)$$

$$\alpha = 1 / (0.12 + 0.08) = 1/0.2$$

Why?

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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$$P(a \mid b) = \frac{P(a,b)}{P(b)}, if P(b) \neq 0$$

d) P(Cavity| toothache v catch) = < P(cavity| toothache v catch), P(~cavity| toothache v catch) >

Let's compute the <u>first term</u> (without using α):

P(cavity| toothache v catch) = P(cavity, (toothache v catch)) / P(toothache v catch)

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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P(toothache v catch) =

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Let's compute the first term (without using α):

P(cavity| toothache v catch) = P(cavity, (toothache v catch)) / P(toothache v catch)

P(toothache v catch) = 0.108 + 0.012 + 0.016 + 0.064 + 0.072 + 0.144 = 0.416

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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Let's compute the first term (without using α):

 $P(\text{cavity}|\text{ toothache } v \text{ catch}) = \underline{P(\text{cavity}, (\text{toothache } v \text{ catch}))} / P(\text{toothache } v \text{ catch})$

P(toothache v catch) = 0.108 + 0.012 + 0.016 + 0.064 + 0.072 + 0.144 = 0.416

P(cavity, (toothache v catch)) =

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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cavity	.108	.012	.072	.008
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$$P(a \mid b) = \frac{P(a,b)}{P(b)}, if P(b) \neq 0$$

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$$P(a \mid b) = \frac{P(a,b)}{P(b)}, if P(b) \neq 0$$

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P(toothache v catch) = 0.108 + 0.012 + 0.016 + 0.064 + 0.072 + 0.144 = 0.416

P(cavity, (toothache v catch)) = 0.108 + 0.012 + 0.072 = 0.192

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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P(toothache v catch) = 0.108 + 0.012 + 0.016 + 0.064 + 0.072 + 0.144 = 0.416

P(cavity, (toothache v catch)) = 0.108 + 0.012 + 0.072 = 0.192

=> P(cavity| toothache v catch) = 0.192 / 0.416 = 0.4615

Consider the dental example discussed at the lecture; its full joint probability distribution is shown below:

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=> P(cavity | toothache v catch) = 0.192 / 0.416 = 0.4615

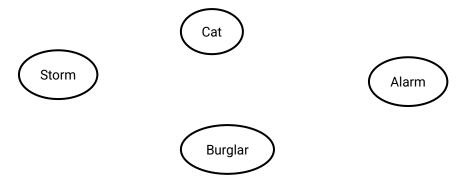
Your task: Compute the second term: P(~cavity| toothache v catch)

(Based on J. Kelleher, B. McNamee and A. D'Arcy, Fundamentals of ML for Predictive Data Analytics, MIT, 2015)

- 1. Stormy nights are rare.
- 2. Burglary is also rare, and if it is a stormy night, burglars are likely to stay at home (burglars don't like going out in storms).
- 3. Cats don't like storms either, and if there is a storm, they like to go inside.
- 4. The alarm on your house is designed to be triggered if a burglar breaks into your house, but sometimes it can be triggered by your cat coming into the house, and sometimes it might not be triggered even if a burglar breaks in (it could be faulty or the burglar might be very good).
- a) Define the topology of a Bayesian network that encodes these relationships.

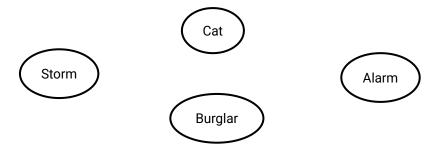
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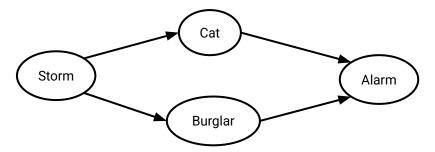
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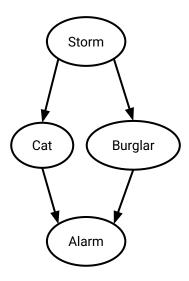
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- a) Define the topology of a Bayesian network that encodes these relationships.



b) Using the data from the table below, create the Conditional Probability Tables (CPTs) for the Bayesian network from the previous step.

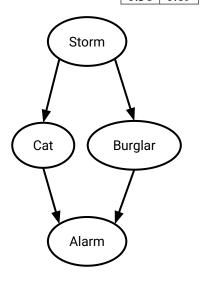
ID	STORM	BURGLAR	Сат	ALARM
1	false	false	false	false
2	false	false	false	false
3	false	false	false	false
4	false	false	false	false
5	false	false	false	true
6	false	false	true	false
7	false	true	false	false
8	false	true	false	true
9	false	true	true	true
10	true	false	true	true
11	true	false	true	false
11	true	false	true	false
13	true	true	false	true



b) Using the data from the table below, create the Conditional Probability Tables (CPTs) for the Bayesian network from the previous step.

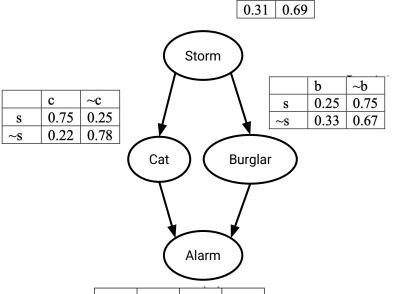
ID	STORM	BURGLAR	CAT	ALARM
1	false	false	false	false
2	false	false	false	false
3	false	false	false	false
4	false	false	false	false
5	false	false	false	true
6	false	false	true	false
7	false	true	false	false
8	false	true	false	true
9	false	true	true	true
10	true	false	true	true
11	true	false	true	false
11	true	false	true	false
13	true	true	false	true

S	~s
0.31	0.69



b) Using the data from the table below, create the Conditional Probability Tables (CPTs) for the Bayesian network from the previous step.

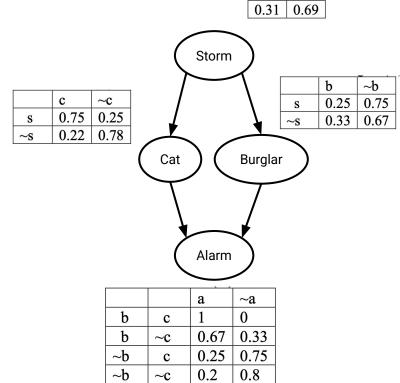
ID	STORM	BURGLAR	CAT	ALARM
1	false	false	false	false
2	false	false	false	false
3	false	false	false	false
4	false	false	false	false
5	false	false	false	true
6	false	false	true	false
7	false	true	false	false
8	false	true	false	true
9	false	true	true	true
10	true	false	true	true
11	true	false	true	false
11	true	false	true	false
13	true	true	false	true



~s

		a	~a
b	c	1	0
b	~c	0.67	0.33
~b	c	0.25	0.75
~b	~c	0.2	0.8

c) Compute the probability that the alarm will be on, given that there is a storm but we don't know if a burglar has broken in or where the cat is.



~s

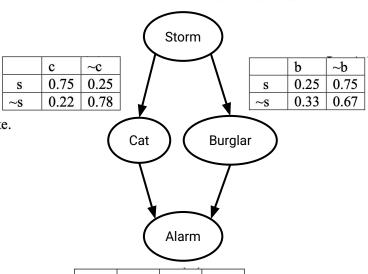
c) Compute the probability that the alarm will be on, given that there is a storm but we don't know if a burglar has broken in or where the cat is.

S	~s
0.31	0.69

We need to compute P(A=true| S=true).

$$P(a \mid s) = \frac{P(a,s)}{P(s)} = \frac{\sum_{b,c} P(a,s,B_b,C_c)}{P(s)}$$

B and C are the hidden variables; $\sum B_b$ means summation over the different values B can take.



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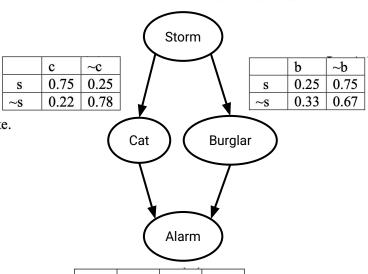
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