

Advanced Artificial Intelligence Revision

Inference Using Full Joint Distribution

| | <i>toothache</i> | | \neg <i>toothache</i> | |
|--|------------------|---------------------|-------------------------|---------------------|
| | <i>catch</i> | \neg <i>catch</i> | <i>catch</i> | \neg <i>catch</i> |
| <i>cavity</i> | 0.108 | 0.012 | 0.072 | 0.008 |
| \neg <i>cavity</i> | 0.016 | 0.064 | 0.144 | 0.576 |
| A full joint distribution for <i>toothache</i> , <i>cavity</i> , <i>catch</i> world. | | | | |

Probabilistic inference is a computation from observed evidence of **posterior probabilities** for **query propositions**. One task involved for accomplishing this is to extract the distribution over a subset of variables or a single variable, hence one way to do this is through **marginal probability**.

Marginalisation/Summing Out - posterior probabilities are summed out, therefore providing the following general **marginalisation rule**:

$$P(Y) = \sum_z P(Y, z)$$

Otherwise can be described as, a distribution over **Y** can be calculated by summing out the posterior probabilities from any joint distribution which contains **Y**.

This rule can also be applied through **conditional probabilities** instead of **joint probabilities**.

$$P(Y) = \sum_z P(Y|z), P(z)$$

This rule is known as **conditioning**. **Marginalisation** and **conditioning** are useful for all kinds of derivations involving probability expressions. In most cases, computation of **conditional probabilities** of some variables given others is preferred.

Conditional probabilities can be found by first calculating the **product rule** to obtain an expression in terms of **unconditional probabilities** and then evaluating the expression from the **full joint distribution**.

For example, the probability of a cavity given evidence of a toothache can be calculated like the following:

$$P(\text{cavity}|\text{toothache}) = \frac{P(\text{cavity} \wedge \text{toothache})}{P(\text{toothache})}$$

To check, the **complement** of this rule would also be calculated to check the validity of the results. The results of which should add to 1.0. Otherwise, a **normalisation constant** may be required.

$$P(\neg \text{cavity}|\text{toothache}) = \frac{P(\neg \text{cavity} \wedge \text{toothache})}{P(\text{toothache})}$$

This can also be written with a **normalisation constant** α , to ensure that the final probabilities will sum to 1.0. The previous equation can be rewritten with a normalisation constant like the following:

$$P(X|e) = \alpha P(X, e) = \alpha \sum_y P(X, e, y)$$

Where X == the query variable; cavity, E == set of observed evidence variables; toothache, Y == remaining unobserved variables; catch.

For example:

$$\begin{aligned} P(\text{cavity}|\text{toothache}) &= \alpha P(\text{cavity}|\text{toothache}) \\ &= \alpha [P(\text{cavity}, \text{toothache}, \text{catch}) + P(\text{cavity}, \text{toothache}, \neg \text{catch})] \\ &= \alpha [< 0.108, 0.016 > + < 0.012, 0.064 >] = \alpha < 0.12, 0.08 > = < 0.6, 0.4 > \end{aligned}$$