

1. Derive the expression for multiple propositions in terms of probabilities of single propositions:

$$p(XYZ|I) = p(X|I) \cdot p(Y|XI) \cdot p(Z|XYI) \quad (4)$$

$$P(X, Y, Z | I) = P(X | I) P(Y | X, I) = P(X | I) P(Y | X, I) P(Z | XY, I)$$

3. As a corollary of Eq. (2), prove Bayes' theorem:

$$p(Y|X, I) = \frac{p(X|Y, I) \cdot p(Y|I)}{p(X|I)} \quad (9)$$

Given 3 statements A, B and I, we know that  $p(A|B, I) = p(B|A, I)$ ,  $\Rightarrow$   
 $\Rightarrow p(A|B, I) \cdot p(B, I) = p(B|A, I) \cdot p(A, I)$ ,  $\Rightarrow p(A|B, I) = \frac{p(B|A, I) \cdot p(A, I)}{p(B, I)}$

2. Manipulating Eqs. (1-2), obtain the *marginalization* rule in the case of a complete discrete set of alternatives:

$$p(X|I) = \sum_k p(XY_k|I) \quad (5)$$

where a *complete set* is a set of events which respect the normalization condition:

$$\sum_k p(Y_k|X, I) = 1 \quad (6)$$

for a given  $Y_k$  we have:  $p(X, Y_k|I) = p(Y_k|X, I) p(X|I)$

$$\Rightarrow \sum_k p(X, Y_k|I) = \sum_k p(Y_k|X, I) p(X|I) = p(X|I) \underbrace{\sum_k p(Y_k|X, I)}_{=1}$$

$$\Rightarrow \boxed{p(X|I) = \sum_k p(X, Y_k|I)}$$

integration over all possible  $\vec{\theta}$

4. (a) Use Bayes' theorem to derive the connection between the evidence, the likelihood and the prior:

$$p(D|H, I) = \int d\vec{\theta} p(\vec{\theta}|H, I) \cdot p(D|\vec{\theta}, H, I) \quad (12)$$

- (b) Re-derive the equation above, but now using the marginalisation rule.

a)

$$\int p(\vec{\theta}'|D, H, I) d\vec{\theta}' = 1 \quad \Rightarrow \quad \int \frac{p(\vec{\theta}'|H, I) p(D|\vec{\theta}', H, I)}{p(D|H, I)} d\vec{\theta}' = 1$$

$$\Rightarrow \int p(\vec{\theta}'|H, I) p(D|\vec{\theta}', H, I) d\vec{\theta}' = p(D|H, I)$$

b) Marginalization rule  $p(D|H, I) = \int d\vec{\theta}' p(\vec{\theta}', D|H, I)$

we have

$$p(\vec{\theta}', D|H, I) = p(D|\vec{\theta}', H, I) p(\vec{\theta}'|H, I)$$

$$\therefore p(D|H, I) = \int d\vec{\theta}' p(\vec{\theta}'|H, I) p(D|\vec{\theta}', H, I)$$

5. (a) Derive the posterior probability for multiple datasets ( $D_1, D_2$ ):

$$p(H|D_1, D_2, I) = p(D_2|H, D_1, I) \cdot p(H|D_1, I) \quad (13)$$

- (b) What does this equation tell us on an inference process which is performed sequentially (i.e. first analysing  $D_1$ , then  $D_2$ ) on multiple datasets, compared to analysing all dataset at the same time?

- (c) How does the expression above change when the two datasets are independent?

a)

$$p(H, D_1, D_2|I) = p(H|D_1, D_2, I) p(D_1, D_2|I)$$

However this is equivalent to  $p(H, D_1, D_2|I) =$

$$= p(D_2|H, D_1, I) p(H, D_1|I) = p(D_2|H, D_1, I) \cdot p(H|D_1, I) \cdot p(D_1|I)$$

$$\Rightarrow p(H|D_1, D_2, I) = \frac{p(H, D_1, D_2|I)}{p(D_1, D_2|I)} = \frac{p(D_2|H, D_1, I) p(H|D_1, I) p(D_1|I)}{p(D_2|D_1, I) p(D_1|I)}$$

$$= \frac{P(D_2 | H, D_1, \mathcal{I}) \cdot P(H | D_1, \mathcal{I})}{P(D_2 | D_1, \mathcal{I})}$$

b) Note that  $P(H | D_1, \mathcal{I})$  is the prior on the first dataset. Thus, we can use the posterior of the so far analyzed datasets, as a prior for the new dataset. If the datasets  $D_1$  and  $D_2$  are independent, then  $P(D_2 | H, D_1, \mathcal{I}) = P(D_2 | H, \mathcal{I})$  and the above expression becomes:

$$c) \quad P(H | D_1, D_2, \mathcal{I}) = \frac{P(D_2 | H, \mathcal{I}) \cdot P(H | D_1, \mathcal{I})}{P(D_2 | \mathcal{I})}$$

6. As a corollary to both Eq.s(1,2), prove the expression for the sum ("or"):

$$p(X + Y|I) = p(X|I) + p(Y|I) - p(XY|I) \quad (14)$$

**Hint** – Think how to relate "X+Y" to products of the X, Y propositions and their negations, which can be then manipulated using the rules of logic.

From a logical perspective, the phrase "X or Y" is equivalent to the phrase

"X and Y or X and not Y or not X and Y". Or expressed mathematically:  $X + Y = XY + X\bar{Y} + \bar{X}Y$

Now each of the products of Y and X are mutually exclusive and can thus be manipulated by the product rule:

$$\begin{aligned}
 p(X+Y|I) &= p(XY|I) + p(\bar{X}Y|I) + p(X\bar{Y}|I) = \\
 &= p(X|Y, I) p(Y|I) + p(\bar{X}|Y, I) p(Y|I) + p(X|\bar{Y}, I) p(\bar{Y}|I) \\
 &= p(Y|I) \underbrace{[p(X|Y, I) + p(\bar{X}|Y, I)]}_1 + p(X|\bar{Y}, I) p(\bar{Y}|I) \\
 &= p(Y|I) + p(X|\bar{Y}, I) p(\bar{Y}|I) \quad \text{commutativity} \\
 &= p(Y|I) + p(\bar{Y}|X, I) p(X|I) \quad \leftarrow \\
 &= p(Y|I) + \underbrace{(1 - p(Y|X, I))}_{p(\bar{Y}|X, I) + p(\bar{Y}|X, I) = 1} p(X|I) \\
 &= p(Y|I) + p(X|I) - \underbrace{p(Y|X, I) p(X|I)}_{p(X, Y|I)} \\
 &= \boxed{p(Y|I) + p(X|I) - p(X, Y|I)}
 \end{aligned}$$