

Computational Intelligence 2008–2009

Tutorial I-a

Peter Lucas, Marina Velikova and Nivea de Carvalho-Ferreira
Institute for Computing and Information Sciences
University of Nijmegen

Elementary probability theory

We adopt the following notations with respect to probability distributions and Boolean variables. Let X denote a variable; if X is a *binary* variable, e.g. taking either the value *true* or *false*, $X = \text{true}$ is also denoted by simply x ; similarly, $X = \text{false}$ is also referred to by $\neg x$.

Furthermore, when it is not really important to know what value a variable takes, we just refer to the variable itself. For example, $P(X)$ either stands for $P(x)$ or $P(\neg x)$. Of course, a statement like $P(X) = 0.7$ would be silly, as in this case it does matter where X really stands for: if it would be x , then $P(x) = 0.7$ and $P(\neg x) = 0.3$, and if it would be $\neg x$, then $P(\neg x) = 0.7$ and $P(x) = 0.3$.

Finally, the expression $\sum_X P(X)$ means summing over all possible values of the variable X ; if X is binary, then

$$\sum_X P(X) = P(x) + P(\neg x)$$

This notation can be generalised for joint probability distributions, e.g.

$$\sum_{X,Y} P(X, Y, a) = P(x, y, a) + P(\neg x, y, a) + P(x, \neg y, a) + P(\neg x, \neg y, a)$$

Of course, the same notation can also be used for conditional probability distributions, as those conform to the axioms of probability theory as well:

$$\sum_X P(X | Y) = P(x | Y) + P(\neg x | Y)$$

Exercise 1

Let P be a probability distribution defined on the set of Boolean expressions \mathcal{B} , i.e. the following axioms hold for P :

- $P(\top) = 1$;
- $P(\perp) = 0$;
- $P(x \vee y) = P(x) + P(y)$, if $x \wedge y = \perp$, i.e. x and y are disjoint, $x, y \in \mathcal{B}$.

a. Draw a Venn diagram with x , y and $x \wedge y$, for the case that $x \wedge y \neq \perp$.

b. Now prove that the following holds in general:

$$P(x \vee y) = P(x) + P(y) - P(x \wedge y)$$

Exercise 2

Let P be a *joint* probability distribution, defined as follows (note that $P(A, B)$ is a shorthand for $P(A \wedge B)$).

$$\begin{aligned} P(a, b) &= 0.3 & P(\neg a, b) &= 0.2 \\ P(a, \neg b) &= 0.4 & P(\neg a, \neg b) &= 0.1 \end{aligned}$$

- Compute $P(a)$ and $P(b)$.
- Compute $P(a | b)$.
- Using these last results, use Bayes' rule to compute $P(b | a)$.

Exercise 3

a. Proof that Bayes' rule holds, based on the definition of conditional probabilities:

$$P(X | Y) = \frac{P(Y | X)P(X)}{P(Y)}$$

- Why is this rule sometimes called the *arc reversal* rule?
- Let $P(B | A_1, \dots, A_n)$ be a conditional probability distribution. Explain why computing $P(B | A_1, \dots, A_n)$ may be computationally hard, and discuss possible solutions.

Exercise 4

Consider joint probability distribution $P(X_1, X_2, X_3, X_4)$:

$$\begin{aligned} P(x_1, x_2, x_3, x_4) &= 0.1 \\ P(x_1, \neg x_2, x_3, x_4) &= 0.04 \\ P(x_1, x_2, \neg x_3, x_4) &= 0.03 \\ P(x_1, x_2, x_3, \neg x_4) &= 0.1 \\ P(\neg x_1, x_2, x_3, x_4) &= 0.0 \\ P(\neg x_1, \neg x_2, x_3, x_4) &= 0.2 \\ P(\neg x_1, x_2, \neg x_3, x_4) &= 0.08 \\ P(\neg x_1, x_2, x_3, \neg x_4) &= 0.1 \\ P(x_1, \neg x_2, \neg x_3, x_4) &= 0.015 \\ P(x_1, \neg x_2, x_3, \neg x_4) &= 0.1 \\ P(x_1, x_2, \neg x_3, \neg x_4) &= 0.004 \\ P(\neg x_1, \neg x_2, \neg x_3, x_4) &= 0.005 \\ P(\neg x_1, \neg x_2, x_3, \neg x_4) &= 0.01 \end{aligned}$$

$$\begin{aligned}
P(\neg x_1, x_2, \neg x_3, \neg x_4) &= 0.01 \\
P(x_1, \neg x_2, \neg x_3, \neg x_4) &= 0.006 \\
P(\neg x_1, \neg x_2, \neg x_3, \neg x_4) &= 0.2
\end{aligned}$$

- a. Compute $P(x_2 \vee \neg x_3 \mid x_1 \wedge x_4)$.
- b. Split up $P(X_1, X_2, X_3, X_4)$ into three factors, and compute the values of these factors for $X_j = \top$, $j = 1, \dots, 4$.

Exercise 5

Let X , Y and Z three different stochastic variables. Assume that X is conditionally independent of Y given Z .

- a. Try to define a probability distribution $P(X \mid Y, Z)$ (i.e. supply the numbers for that distribution) for which the conditional independence property holds.
- b. Proof that from $P(X \mid Y, Z) = P(X \mid Z)$ it follows that $P(Y \mid X, Z) = P(Y \mid Z)$.

Exercise 6

- a. Prove that if the sets of variables \mathbf{X} and \mathbf{Y} are conditionally independent given the set of variables \mathbf{Z} , i.e.

$$P(\mathbf{X} \mid \mathbf{Y}, \mathbf{Z}) = P(\mathbf{X} \mid \mathbf{Z})$$

it follows that

$$P(\mathbf{X}, \mathbf{Y} \mid \mathbf{Z}) = P(\mathbf{X} \mid \mathbf{Z})P(\mathbf{Y} \mid \mathbf{Z})$$

- b. Explain why the use of marginalisation is often combined with conditioning.

Exercise 7

There are three prisoners, A , B , and C . Two of them will be released and one will be executed. A asks the warden to tell him the name of one of the others in his cohort who will be released. As the question is not directly about A 's fate, the warden obliges and says, " B will be released." Assuming the warden's truthfulness, what are A 's and C 's respective probabilities of dying now? (*Three Prisoners Problem - Martin Gardner*)