

Probabilistic Artificial Intelligence

Problem Set 1 Solutions

September 28, 2018

1. Conditional Independence

Consider the following joint distribution for three random variables, $a, b, c \in \{0, 1\}$.

a	b	c	$p(a, b, c)$
0	0	0	0.192
0	0	1	0.144
0	1	0	0.048
0	1	1	0.216
1	0	0	0.192
1	0	1	0.064
1	1	0	0.048
1	1	1	0.096

Show that a and b are dependent, namely $p(a, b) \neq p(a)p(b)$. But, they are marginally independent given c , namely $p(a, b | c) = p(a | c)p(b | c)$. (c.f. Bishop *Pattern Recognition and Machine Learning*, Exercise 8.3)

Solution. For $p(a, b) \neq p(a)p(b)$ it suffices to simply produce example values for which the two expressions differ. Let $a = 0, b = 0$. Then by marginalizing on c ,

$$p(a = 0, b = 0) = 0.192 + 0.144 = 0.336$$

Where as by marginalizing on b, c ,

$$p(a = 0) = 0.192 + 0.144 + 0.048 + 0.216 = 0.6$$

And by marginalizing on a, c ,

$$p(b = 0) = 0.192 + 0.144 + 0.192 + 0.064 = 0.592$$

Thus we can show $p(a = 0) \cdot p(b = 0) = 0.6 \cdot 0.592 = 0.3552 \neq 0.336$.

To show $p(a, b | c) = p(a | c)p(b | c)$, we need to show that it holds for every value of a, b, c . Note that $p(c = 0) = 0.192 + 0.048 + 0.192 + 0.048 = 0.48$.

For the case when $a = 0, b = 0, c = 0$,

$$p(a = 0, b = 0 | c = 0) = 0.192 / 0.48 = 0.4$$

a	b	$p(a, b, c)$
0	0	0.4
0	1	0.1
1	0	0.4
1	1	0.1

Table 1: $p(a, b|c = 0)$

a	b	$p(a, b, c)$
0	0	0.27692308
0	1	0.41538462
1	0	0.12307692
1	1	0.18461538

Table 2: $p(a, b|c = 1)$

and

$$p(a = 0|c = 0)p(b = 0|c = 0) = (0.192 + 0.048)/0.48 \cdot (0.192 + 0.192)/0.48 = 0.4$$

Which are equal.

More generally, we can take the entire table and divide it by $p(c = 0)$ and $p(c = 1)$ to get the conditional distributions $p(a, b|c = 0)$ (Table 1) and $p(a, b|c = 1)$ (Table 2) respectively. We can then use these tables to look up the relevant values.

2. Bayes Rule

A routine breast cancer mammography screening is performed on a group of people of age forty. 1% of the participants in the screening actually have breast cancer. 80% of the people in the screening with breast cancer received positive results (has breast cancer) on the mammography test. 9.6% of people without breast cancer received a positive result on their mammographies. Suppose a person of this age receives a positive result on their mammography. Given the information in this screening, what is the probability that he has breast cancer?

Solution. Our goal is to estimate, $P(C = 1|T = 1)$ where C means cancer and T means mammography (test). Using Bayes Rule,

$$P(C = 1|T = 1) = \frac{P(T = 1|C = 1)P(C = 1)}{P(T = 1)}$$

where $P(T = 1) = P(T = 1|C = 0)P(C = 0) + P(T = 1|C = 1)P(C = 1)$.

Thus using the values provided in the question,

$$P(C = 1|T = 1) = \frac{0.8 \cdot .01}{.096 \cdot .99 + .8 \cdot .01} \approx .077$$

3. Chain rule

Derive the chain rule from the basic rules of probability. (Hint: by the definition of conditional probability $P(A, B) = P(A | B)P(B)$). How many factorizations are possible for a distribution on n random variables?

Solution. The chain rule states that

$$P(A_1, \dots, A_n) = P(A_1)P(A_2|A_1)P(A_3|A_2, A_1) \dots P(A_n|A_{n-1}, \dots, A_1)$$

By induction. In the case of $n = 2$ we have simply the definition of conditional probability. Assume true for the n -th case. Consider the $n+1$ -th case. Again by the definition of conditional probability,

$$P(A_1, \dots, A_n, A_{n+1}) = P(A_{n+1}|A_1, \dots, A_n)P(A_1, \dots, A_n)$$

expand the term $P(A_1, \dots, A_n)$ using the inductive assumption.

To see that there are $n!$ ways to factor a distribution on n random variables, consider an iterative process where at each step you choose to “factor out” a specific variable. For example, at step 1 you factor out A_1 resulting in $P(A_1)P(A_2, \dots, A_n|A_1)$. Now you have $n - 1$ choices left for which variable to factor out. For example, suppose you choose number 42 resulting in $P(A_1)P(A_{42}|A_2, \dots, A_{41}, A_{43}, \dots, A_n)P(A_{42}|A_2, \dots, A_{41}, A_{43}, \dots, A_n)$. Now you have $n - 2$ remaining choices for the next factorization.