

Artificial Intelligence II

Why multiplication of factors works

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1 Introduction

These notes provide a simple explanation of why the multiplication of factors in the manner suggested works, and why it avoids duplicating the computation of sub-expressions.

1.1 Why it works

Let's drop any reference to probabilities for the moment and just look at general summations involving functions. Say you have three finite sets $X = \{x_1, \dots, x_p\}$, $Y = \{y_1, \dots, y_q\}$ and $Z = \{z_1, \dots, z_r\}$, and you want to compute a summation like

$$f(x, y) = \sum_{z \in Z} g(x, y, z)h(y, z) \quad (1)$$

for values $x \in X$ and $y \in Y$. The sum will look like

$$f(x, y) = g(x, y, z_1)h(y, z_1) + \dots + g(x, y, z_r)h(y, z_r)$$

In other words, the products you need to compute are the ones *for which values of z coincide*. This, in a nutshell, is what the process of combining factors achieves. In this example, we would write the factors in the sum as

x	y	z	$F_x(x, y, z)$
x_1	y_1	z_1	$g(x_1, y_1, z_1)$
x_1	y_1	z_2	$g(x_1, y_1, z_2)$
\vdots	\vdots	\vdots	\vdots
x_p	y_q	z_r	$g(x_p, y_q, z_r)$

and

y	z	$F_y(y, z)$
y_1	z_1	$h(y_1, z_1)$
y_1	z_2	$h(y_1, z_2)$
\vdots	\vdots	\vdots
y_q	z_r	$h(y_q, z_r)$

When the factors are multiplied we match up and multiply the table entries for which variables common to both have matching values. So for example

x	y	z	$F_{x,y}(x, y, z)$
x_1	y_1	z_1	$g(x_1, y_1, z_1)h(y_1, z_1)$
x_1	y_1	z_2	$g(x_1, y_1, z_2)h(y_1, z_2)$
\vdots	\vdots	\vdots	\vdots
x_p	y_q	z_r	$g(x_p, y_q, z_r)h(y_q, z_r)$

In order to deal with the summation to form the factor $F_{x,y}(x, y)$ we now form sums of the entries in $F_{x,y}(x, y, z)$ over all values for z , so

x	y	$F_{x,y}(x, y)$
x_1	y_1	$\sum_{z \in Z} F_{x,y}(x_1, y_1, z)$
x_1	y_2	$\sum_{z \in Z} F_{x,y}(x_1, y_2, z)$
\vdots	\vdots	\vdots
x_p	y_q	$\sum_{z \in Z} F_{x,y}(x_p, y_q, z)$

Expanding out one of these summations results in something like

$$F_{x,y}(x_1, y_2) = \sum_{z \in Z} g(x_1, y_2, z)h(y_2, z) \quad (2)$$

Comparing equations 1 and 2 we see that the entries in the factor $F_{x,y}(x, y)$ are just the values of the summation for each possible pair of values x and y .

1.2 The relationship to probabilities

So: the tabular process using factors is just a way of keeping track of the values needed to compute the sum. In the probabilistic inference algorithm the functions f , g , h and so on are all just (conditional) probability distributions, and because we're dealing the the decomposition

$$\Pr(X_1, \dots, X_n) = \prod_{i=1}^n \Pr(X_i | \text{parents}(X_i))$$

on a directed, acyclic graph we start off with a factor for each RV, and each time we get to a summation we sum out the corresponding variable. (The above example does not have this structure, which is why the summing out notation $F_{x,y,\bar{z}}$ does not appear, but the process is identical.)

1.3 Why it avoids duplication

Reverting now to probabilities, say we have a Bayes network that represents the decomposition

$$\Pr(X, Y_1, Y_2, E_1, E_2) = \Pr(E_1 | Y_1, Y_2) \Pr(E_2 | Y_2) \Pr(Y_2 | X) \Pr(X) \Pr(Y_1)$$

(Exercise: draw it.) Now we attempt to compute the inference

$$\Pr(X | e_1, e_2) = \frac{1}{Z} \Pr(X) \sum_{y_1 \in Y_1} \Pr(Y_1) \sum_{y_2 \in Y_2} \Pr(Y_2 | X) \Pr(e_1 | Y_1, Y_2) \Pr(e_2 | Y_2)$$

The repetition of computations arises in summations like this because—handled in the naive way using recursive depth-first evaluation—the summation

$$\sum_{y_2 \in Y_2} \Pr(Y_2 | X) \Pr(e_1 | Y_1, Y_2) \Pr(e_2 | Y_2)$$

will involve computing the product $\Pr(Y_2 | X) \Pr(e_2 | Y_2)$ for each value of Y_1 . This problem will repeat itself for each value of X . By computing and storing each of the products needed only once the method based on factors avoids this.