MPE proof

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Theorem 0.1. Given the definition of Most Probable Explanation (MPE):

$$MPE(e) = \operatorname*{arg\,max}_{q} \mathbb{P}(Q = q | E = e) \tag{1}$$

the following algorithm constructs the branch corresponding to the MPE in a Bayesian Network composed of the set of nodes $V = \{Y_1 \dots Y_N\}$:

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\label{eq:Result: Sequence of nodes corresponding to MPE} \begin{split} E &:= Y_1; \\ \text{branch} &= \emptyset; \\ \textbf{while} &\ E \neq V \ \textbf{do} \\ & | \ & \text{append arg} \max_{Y_k} \mathbb{P}(Y_k|E) \ \text{to branch}; \\ & E &= E \cup \text{arg} \max_{Y_k} \mathbb{P}(Y_k|E); \\ \textbf{end} \end{split}
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Proof. By backwards analysis, we can reconstruct the steps followed by the algorithm.

In the last step we are calculating the probability:

$$\max_{y_N} \mathbb{P}(Y_N | Y_{N-1} \dots Y_1) \tag{2}$$

To arrive in that state, in the previous step we calculated:

$$\max_{y_{N-1}} \mathbb{P}(Y_{N-1}|Y_{N-2}\dots Y_1) \tag{3}$$

and so on to arrive to the initial step:

$$\max_{y_2} \mathbb{P}(Y_2|Y_1) \tag{4}$$

The total probability of the branch is:

$$\max_{y_N} \mathbb{P}(Y_N | Y_{N-1} \dots Y_1) \\
\times \max_{y_{N-1}} \mathbb{P}(Y_{N-1} | Y_{N-2} \dots Y_1) \\
\times \dots \\
\times \max_{y_2} \mathbb{P}(Y_2 | Y_1) \\
= \max_{y_2} \frac{\mathbb{P}(Y_N, Y_{N-1}, \dots, Y_1)}{\mathbb{P}(Y_{N-1}, \dots, Y_1)} \\
\times \max_{y_N} \frac{\mathbb{P}(Y_N, Y_{N-1}, \dots, Y_1)}{\mathbb{P}(Y_{N-2}, \dots, Y_1)} \\
\times \max_{y_{N-1}} \frac{\mathbb{P}(Y_N, Y_{N-1}, \dots, Y_1)}{\mathbb{P}(Y_N, Y_N, \dots, Y_1)} \\
\times \dots \\
\times \max_{y_2} \frac{\mathbb{P}(Y_2, Y_1)}{\mathbb{P}(Y_1)}$$
(5)

And by a simple cyclic reordering of the denominators where each factor i receives the denominator of term i + 1:

$$= \max_{y_N} \frac{\mathbb{P}(Y_N, Y_{N-1}, \dots, Y_1)}{\mathbb{P}(Y_1)}$$

$$\times \max_{y_{N-1}} \frac{\mathbb{P}(Y_{N-1}, \dots, Y_1)}{\mathbb{P}(Y_{N-1}, \dots, Y_1)}$$

$$\times \dots$$

$$\times \max_{y_2} \frac{\mathbb{P}(Y_2, Y_1)}{\mathbb{P}(Y_2, Y_1)}$$

$$= \max_{y_N} \frac{\mathbb{P}(Y_N, Y_{N-1}, \dots, Y_1)}{\mathbb{P}(Y_1)}$$

$$\times 1$$

$$\times \dots$$

$$\times 1$$

$$= \max_{y_N} \frac{\mathbb{P}(Y_N, Y_{N-1}, \dots, Y_1)}{\mathbb{P}(Y_1)}$$

$$= \max_{y_N} \mathbb{P}(Y_N, \dots, Y_{N-1} | Y_1)$$

$$= \max_{y_N} \mathbb{P}(Y_N, \dots, Y_{N-1} | Y_1)$$

which is exactly the probability of the MPE we were looking for.