FUNDAMENTALS OF ARTIFICIAL INTELLIGENCE

Exercise 8: Bayesian networks – Solutions Josefine Gaßner

Winter Semester 2022/23

Problem 8.1:

a. ii, iii, iv and v.

For v., consider the Markov blanket of *D*.

Remember that a node in the Bayesian network is conditionally independent from all other nodes given its parents, children and children's parents (this evidence is the **Markov blanket** of the node).

- b. $\mathbf{P}(D,TP,CC,UP,PP,W) = \mathbf{P}(D)\mathbf{P}(TP)\mathbf{P}(CC)\mathbf{P}(UP|D,TP)\mathbf{P}(PP|CC,UP)\mathbf{P}(W|CC,UP,PP)$.
- c. To calculate these values we can directly use the equation derived in **b**. In fact, we have to evaluate it using the requested values of the random variables:

$$\begin{split} &P(\neg d, tp, cc, \neg up, pp, w) = P(\neg d)P(tp)P(cc)P(\neg up|\neg d, tp)P(pp|cc, \neg up)P(w|cc, \neg up, pp) = \\ &= 0.75 \cdot 0.35 \cdot 0.3 \cdot 0.9 \cdot 0.9 \cdot 0.9 = 0.05740875. \\ &P(\neg d, tp, cc, \neg up, \neg pp, w) = P(\neg d)P(tp)P(cc)P(\neg up|\neg d, tp)P(\neg pp|cc, \neg up)P(w|cc, \neg up, \neg pp) = \\ &= 0.75 \cdot 0.35 \cdot 0.3 \cdot 0.9 \cdot 0.1 \cdot 0.5 = 0.00354375. \end{split}$$

d. The required probability is $P(w|tp, \neg d, pp)$.

To calculate this we can use enumeration:

$$\mathbf{P}(W|tp,\neg d,pp) = \alpha P(\neg d)\,P(tp)\,\sum_{UP}\mathbf{P}(UP|\neg d,tp)\,\sum_{CC}\mathbf{P}(CC)\,\mathbf{P}(pp|CC,UP)\,\mathbf{P}(W|CC,UP,pp).$$

$$\begin{split} P(w|tp,\neg d,pp) &= \alpha P(\neg d) P(tp) \left\{ P(up|\neg d,tp) \left[P(cc) P(pp|cc,up) P(w|cc,up,pp) \right. \right. \\ &+ P(\neg cc) P(pp|\neg cc,up) P(w|\neg cc,up,pp) \right] \\ &+ P(\neg up|\neg d,tp) \left[P(cc) P(pp|cc,\neg up) P(w|cc,\neg up,pp) \right. \\ &+ P(\neg cc) P(pp|\neg cc,\neg up) P(w|\neg cc,\neg up,pp) \right] \right\} \\ &= \alpha \cdot 0.75 \cdot 0.35 \left\{ 0.1 \left[0.3 \cdot 0.5 \cdot 0.4 + 0.7 \cdot 0.05 \cdot 0.05 \right] + 0.9 \left[0.3 \cdot 0.9 \cdot 0.9 + 0.7 \cdot 0.1 \cdot 0.15 \right] \right\} \\ &\approx \alpha \cdot 0.0615. \end{split}$$

$$\begin{split} P(\neg w|tp,\neg d,pp) &= \alpha P(\neg d) P(tp) \left\{ P(up|\neg d,tp) \left[P(cc) P(pp|cc,up) P(\neg w|cc,up,pp) \right. \right. \\ &\quad + P(\neg cc) P(pp|\neg cc,up) P(\neg w|\neg cc,up,pp) \right] \\ &\quad + P(\neg up|\neg d,tp) \left[P(cc) P(pp|cc,\neg up) P(\neg w|cc,\neg up,pp) \right. \\ &\quad + P(\neg cc) P(pp|\neg cc,\neg up) P(\neg w|\neg cc,\neg up,pp) \right] \right\} \\ &= \alpha \cdot 0.75 \cdot 0.35 \left\{ 0.1 [0.3 \cdot 0.5 \cdot 0.6 + 0.7 \cdot 0.05 \cdot 0.95] + 0.9 [0.3 \cdot 0.9 \cdot 0.1 + 0.7 \cdot 0.1 \cdot 0.85] \right\} \\ &\approx \alpha \cdot 0.0237, \end{split}$$

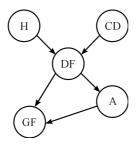
$$\alpha = \frac{1}{0.0615 + 0.0237} \approx 11.7371,$$

$$P(w|tp, \neg d, pp) \approx 11.7371 \cdot 0.0615 \approx 0.7218.$$

e. The random variable EF has a direct influence on the race. We can reasonably assume that when there is an engine failure during the race, the pilot does not win. Another reasonable assumption is that a competitive car is also more reliable with a direct influence on the random variable EF. In conclusion, we introduce the node EF as a parent of W and child of CC.

Problem 8.2:

a. The corresponding network is the following:



b. Using enumeration:

$$\begin{split} \mathbf{P}(CD|\neg a,gf) &= \alpha \mathbf{P}(CD) \sum_{DF} \mathbf{P}(gf|\neg a,DF) \mathbf{P}(\neg a|DF) \sum_{H} \mathbf{P}(DF|CD,H) \mathbf{P}(H). \\ P(cd|\neg a,gf) &= \alpha P(cd) \left\{ P(gf|df,\neg a) P(\neg a|df) \left[P(df|cd,h) P(h) + P(df|cd,\neg h) P(\neg h) \right] \right. \\ &+ P(gf|\neg df,\neg a) P(\neg a|\neg df) \left[P(\neg df|cd,h) P(h) + P(\neg df|cd,\neg h) P(\neg h) \right] \end{split}$$

$$= \alpha \cdot 0.6\{0.4 \cdot 0.3[0.15 \cdot 0.5 + 0.01 \cdot 0.5] + 0.05 \cdot 0.75[0.85 \cdot 0.5 + 0.99 \cdot 0.5]\}$$

 $\approx \alpha \cdot 0.0265$,

$$\begin{split} P(\neg cd | \neg a, gf) &= \alpha P(\neg cd) \left\{ P(gf | df, \neg a) P(\neg a | df) \left[P(df | \neg cd, h) P(h) + P(df | \neg cd, \neg h) P(\neg h) \right] \right. \\ &+ P(gf | \neg df, \neg a) P(\neg a | \neg df) \left[P(\neg df | \neg cd, h) P(h) + P(\neg df | \neg cd, \neg h) P(\neg h) \right] \right\} \\ &= \alpha \cdot 0.4 \left\{ 0.4 \cdot 0.3 [0.99 \cdot 0.5 + 0.1 \cdot 0.5] + 0.05 \cdot 0.75 [0.01 \cdot 0.5 + 0.9 \cdot 0.5] \right\} \\ &\approx \alpha \cdot 0.0330, \end{split}$$

$$\alpha = \frac{1}{0.0265 + 0.0330} \approx 16.8067$$

$$\mathbf{P}(CD|\neg a, gf) \approx 16.8067 \cdot \begin{bmatrix} 0.0265 \\ 0.0330 \end{bmatrix} \approx \begin{bmatrix} 0.4454 \\ 0.5546 \end{bmatrix}.$$

c. Using variable elimination:

$$\mathbf{P}(CD|\neg a,gf) = \underbrace{\alpha P(CD)}_{f_1(CD)} \underbrace{\sum_{DF} \underbrace{P(gf|\neg a,DF)}_{f_2(DF)} \underbrace{P(\neg a|DF)}_{f_3(DF)} \underbrace{\sum_{H} \underbrace{P(DF|CD,H)}_{f_4(DF,CD,H)} \underbrace{P(DF|CD,H)}_{f_5(H)}}_{f_5(H)}.$$

In the following notation we represent a $2 \times 2 \times 2$ matrix as $\{[2 \times 2] [2 \times 2]\}$.

$$\begin{split} \mathbf{f_4}(DF,CD,H) &= \left\{ \begin{array}{ll} \mathbf{P}(DF|CD,h) & \mathbf{P}(DF|CD,\neg h) \end{array} \right\} \\ &= \left\{ \begin{bmatrix} P(df|cd,h) & P(df|\neg cd,h) \\ P(\neg df|cd,h) & P(\neg df|\neg cd,h) \end{array} \right] \begin{bmatrix} P(df|cd,\neg h) & P(df|\neg cd,\neg h) \\ P(\neg df|cd,\neg h) & P(\neg df|\neg cd,\neg h) \end{array} \right] \right\} \\ &= \left\{ \begin{bmatrix} 0.15 & 0.99 \\ 0.85 & 0.01 \end{bmatrix} \begin{bmatrix} 0.01 & 0.1 \\ 0.99 & 0.9 \end{bmatrix} \right\}, \end{split}$$

$$\begin{aligned} \mathbf{f_1}(CD) &= \left[\begin{array}{cc} P(cd) & P(\neg cd) \end{array}\right] = \left[\begin{array}{cc} 0.6 & 0.4 \end{array}\right], \ \mathbf{f_2}(DF) = \left[\begin{array}{cc} P(gf|\neg a,df) \\ P(gf|\neg a,\neg df) \end{array}\right] = \left[\begin{array}{cc} 0.4 \\ 0.05 \end{array}\right], \\ \mathbf{f_3}(DF) &= \left[\begin{array}{cc} P(\neg a|df) \\ P(\neg a|\neg df) \end{array}\right] = \left[\begin{array}{cc} 0.3 \\ 0.75 \end{array}\right], \ \mathbf{f_5}(H) = \left[\begin{array}{cc} P(h) & P(\neg h) \end{array}\right] = \left[\begin{array}{cc} 0.5 & 0.5 \end{array}\right]. \end{aligned}$$

After defining the factors, we can write:

$$\mathbf{P}(CD|\neg a,gf) = \alpha \mathbf{f_1}(CD) \times \sum_{DF} \mathbf{f_2}(DF) \times \mathbf{f_3}(DF) \times \sum_{H} \mathbf{f_4}(DF,CD,H) \times \mathbf{f_5}(H)$$

P(CD|
$$\neg a, gf$$
) = $\alpha \mathbf{f_1}(CD) \times \sum_{DF} \mathbf{f_2}(DF) \times \mathbf{f_3}(DF) \times \sum_{H} \mathbf{f_4}(DF, CD, H) \times \mathbf{f_5}(H)$. In the following we use the pointwise product and we sum out variables.
$$\mathbf{f_4}(DF, CD, H) \times \mathbf{f_5}(H) = \left\{ \begin{bmatrix} 0.075 & 0.495 \\ 0.425 & 0.005 \end{bmatrix} \begin{bmatrix} 0.005 & 0.050 \\ 0.495 & 0.450 \end{bmatrix} \right\},$$

$$\mathbf{f_6}\left(DF,CD\right) = \sum_{H} \mathbf{f_4}\left(DF,CD,H\right) \times \mathbf{f_5}\left(H\right) = \sum_{H} \left\{ \left[\begin{array}{ccc} 0.075 & 0.495 \\ 0.425 & 0.005 \end{array} \right] \left[\begin{array}{ccc} 0.005 & 0.050 \\ 0.495 & 0.450 \end{array} \right] \right\} = \left[\begin{array}{ccc} 0.080 & 0.545 \\ 0.920 & 0.455 \end{array} \right],$$

$$\begin{split} \mathbf{f_2}(DF) \times \mathbf{f_3}(DF) \times \mathbf{f_6}(DF,CD) &= \left[\begin{array}{c} 0.0096 & 0.0654 \\ 0.0345 & 0.0171 \end{array} \right], \\ \mathbf{f_7}(CD) &= \sum_{DF} \mathbf{f_2}(DF) \times \mathbf{f_3}(DF) \times \mathbf{f_6}(DF,CD) = \sum_{DF} \left[\begin{array}{c} 0.0096 & 0.0654 \\ 0.0345 & 0.0171 \end{array} \right] = \left[\begin{array}{c} 0.0441 & 0.0825 \end{array} \right]. \\ \text{And finally we get:} \\ \mathbf{P}(CD|\neg a,gf) &= \alpha \mathbf{f_1}(CD) \times \mathbf{f_7}(CD) \approx \alpha \left[\begin{array}{c} 0.0265 & 0.0330 \end{array} \right], \\ \alpha &= \frac{1}{0.0265+0.0330} \approx 16.8067, \\ \mathbf{P}(CD|\neg a,gf) \approx 16.8067 \cdot \left[\begin{array}{c} 0.0265 & 0.0330 \end{array} \right] \approx \left[\begin{array}{c} 0.4454 & 0.5546 \end{array} \right]. \end{split}$$

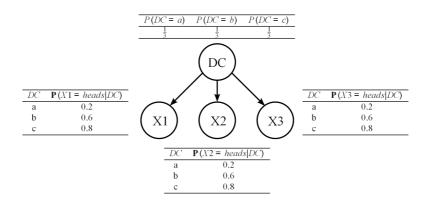
d. Besides the last calculation to complete the normalization that both methods require, we have:

	Enumeration	Variable Elimination
additions	6	6
multiplications	18	16

In this case we do not have a significant improvement using variable elimination. The improvement becomes more significant for larger Bayesian networks.

Problem 8.3:

a. The network is composed of four random variables: The coin that has been drawn DC with domain < a, b, c > and the results of the three flips X1, X2 and X3 with domains < heads, tails >.



b. The required probability is P(DC|X1 = heads, X2 = heads, X3 = tails).

We first write the full joint probability:

$$\mathbf{P}(DC, X1, X2, X3) = \mathbf{P}(X1|DC)\mathbf{P}(X2|DC)\mathbf{P}(X3|DC)\mathbf{P}(DC).$$

The result is directly obtained introducing the evidence and using normalization:

$$\mathbf{P}(DC|X1 = heads, X2 = heads, X3 = tails) =$$

$$= \alpha \mathbf{P}(X1 = heads|DC)\mathbf{P}(X2 = heads|DC)\mathbf{P}(X3 = tails|DC)\mathbf{P}(DC) =$$

$$=\alpha\begin{bmatrix}0.2\\0.6\\0.8\end{bmatrix}\times\begin{bmatrix}0.2\\0.6\\0.8\end{bmatrix}\times\begin{bmatrix}0.8\\0.4\\0.2\end{bmatrix}\times\begin{bmatrix}\frac{1}{3}\\\frac{1}{3}\end{bmatrix}\approx\alpha\begin{bmatrix}0.0107\\0.0480\\0.0427\end{bmatrix},$$

$$\alpha = \frac{1}{(0.0107 + 0.0480 + 0.0427)} \approx 9.8619329,$$

$$\mathbf{P}(DC|X1 = heads, X2 = heads, X3 = tails) \approx 9.8619329 \begin{bmatrix} 0.0107 \\ 0.0480 \\ 0.0427 \end{bmatrix} = \begin{bmatrix} 0.1055 \\ 0.4734 \\ 0.4211 \end{bmatrix}.$$

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The coin that is most likely to have been drawn is b.