Probabilistic Models: Spring 2014 Jointree Example Solutions

We are given the following Bayesian network $G$.


| $S$ | $f_{S}$ |
| :---: | :---: |
| T | .4 |
| F | .6 |


| $A$ | $f_{A}$ |
| :---: | :--- |
| T | .2 |
| F | .8 |


| $A$ | $T$ | $f_{T}$ |
| :---: | :---: | :---: |
| T | T | .3 |
| T | F | .7 |
| F | T | .1 |
| F | F | .9 |


| $S$ | $B$ | $f_{B}$ |
| :--- | :--- | :--- |
| T | T | .6 |
| T | F | .4 |
| F | T | .5 |
| F | F | .5 |


| $T$ | $C$ | $P$ | $f_{P}$ |
| :---: | :---: | :---: | :---: |
| T | T | T | .9 |
| T | T | F | .1 |
| T | F | T | .8 |
| T | F | F | .2 |
| F | T | T | .8 |
| F | T | F | .2 |
| F | F | T | .1 |
| F | F | F | .9 |


| $P$ | $B$ | $D$ | $f_{D}$ |
| :--- | :--- | :--- | :--- |
| T | T | T | .8 |
| T | T | F | .2 |
| T | F | T | .7 |
| T | F | F | .3 |
| F | T | T | .7 |
| F | T | F | .3 |
| F | F | T | .4 |
| F | F | F | .6 |


| $S$ | $C$ | $f_{C}$ |
| :---: | :---: | :---: |
| T | T | .8 |
| T | F | .2 |
| F | T | .1 |
| F | F | .9 |


| $P$ | $X$ | $f_{X}$ |
| :---: | :---: | :---: |
| T | T | .8 |
| T | F | .2 |
| F | T | .1 |
| F | F | .9 |

1. Construct the moral graph $M_{G}$ of $G$

2. Triangulate $M_{G}$ to obtain $T_{G}$. Use the following elimination ordering: $A$, $T, X, D, P, C, B, S$

3. Construct a jointree $J_{G}$ from the triangulated graph. Use the following clusters and factor assignments:

- $A T: f_{A}, f_{T}$
- TCP: $f_{P}$
- $C P B$ : trivial factor (value 1)
- CSB: $f_{C}, f_{S}, f_{B}$
- $P B D: f_{D}$
- $P X: f_{X}$
- Connect $P X$ to $T C P$

4. Use $J_{G}$ to calculate the following probabilities. Use $C P B$ as the root.
(a) $P(C)$

All of the messages:

| $T$ | $M_{A T, T C P}$ |
| :--- | :--- |
| T | .1400 |
| F | .8600 |

We find this by marginalizing $A$ from $f_{A T}$ because we project $f_{A T}$ onto the separator between $A T$ and $T C P$, which is $T$.

| $P$ | $M_{P X, T C P}$ |
| ---: | :--- |
| T | 1 |
| F | 1 |

We find this by marginalizing $X$ from $f_{P X}$ because we project $f_{P X}$ onto the separator between $P X$ and $T C P$, which is $P$.

| $C$ | $P$ | $M_{T C P, C P B}$ |
| :---: | :---: | :--- |
| T | T | .8140 |
| T | F | .1860 |
| F | T | .1980 |
| F | F | .8020 |

We find this by multiplying the incoming messages to $T C P$ by $f_{T C P}$, i.e. $f_{T C P} M_{A T, T C P} M_{P X, T C P}$. Then, we project that value onto the separator between $T C P$ and $C P B$, which is $C P$.

- | $P$ | $B$ | $M_{P D B, C P B}$ |
| :--- | :--- | :--- |
| T | T | 1 |
| T | F | 1 |
| F | T | 1 |
| F | F | 1 |

We find this by projecting $f_{P D B}$ onto the separator between $P D B$ and $C P B$, which is $P B$.

| $B$ | $C$ | $M_{C S B, C P B}$ |
| :---: | :---: | :--- |
| T | T | .2220 |
| T | F | .3180 |
| F | T | .1580 |
| F | F | .3020 |

We find this by projecting $f_{C S B}$ onto the separator between $C S B$ and $C P B$, which is $C B$.

- | $C$ | $P(C)$ |
| :---: | :---: |
| T | .3800 |
| F | .6200 |

We find this by multiplying all of the incoming messages to $C P B$ by $f_{C P B}$. Note that multipying factor $f$ by the trivial factor just results in $f$ scaled by the trivial factor ( 1 , in this case). So, the final distribution over the cluster is: $M_{T C P, C P B} M_{P D B, C P B} M_{C S B, C P B}$. Finally, we project that onto $C$ since that was the original query.
(b) $P(C, B=\mathrm{T}) \quad$ Add an evidence factor to $C S B$. Also, consider which messages can be reused.
The only message which changes is the message from $C S B$ to $C P B$. All of the others can be reused. We first add the evidence factor (which assigns 1 to $B=T$ and 0 to $B=F$ ) to $f_{C S B}$. We then compute its message to $C P B$ as normal.

| $B$ | $C$ | $M_{C S B, C P B}$ |
| :--- | :--- | :--- |
| T | T | .2220 |
| T | F | .3180 |
| F | T | .0000 |
| F | F | .0000 |

We then recalculate the distribution over $C P B$, which is again: $M_{T C P, C P B} M_{P D B, C P B} M_{C S B, C P B}$.
Finally, we project onto $C$ (optionally also $B$, but some of the values will just be 0 , so we can leave those off).

| $B$ | $C$ | $P(C, B=\mathrm{T})$ |
| :--- | :--- | :--- |
| T | T | .2220 |
| T | F | .3180 |

In general, the joint probabilities will not be the same as the message.
(c) $P(C \mid B=\mathrm{T}) \quad$ Consider which messages can be reused.

In this case, we can reuse all of the previous messages because no new evidence was added to the problem. Consequently, we can find the probability of the evidence by projecting $P(C, B=\mathrm{T})$ onto $\emptyset$. (You can also think of this as projecting onto $B$, but $P(B=\mathrm{F})$ is always 0 ).

| - | $P(B=\mathrm{T})$ |
| :--- | :--- |
| T | .5400 |

We can then use Bayes rule to calculate $P(C \mid B=\mathrm{T})=\frac{P(C, B=\mathrm{T})}{P(B=\mathrm{T})}$

| $B$ | $C$ | $M_{C S B, C P B}$ |
| :---: | :---: | :--- |
| T | T | .4111 |
| T | F | .5889 |

## Some useful equations and things

```
procedure FactorElimination(elimination tree T, evidence e)
    for each variable E E e do
            i\leftarrow node in T such that E\in C}\mp@subsup{\mathbf{C}}{i}{
            \phi}\leftarrow\mp@subsup{\psi}{i}{}\mp@subsup{\lambda}{E}{}\quad\triangleright\mathrm{ adding the evidence to node }
        end for
        Choose a root node r in T
        Pull messages towards r
        Push messages away from r
        return }\mp@subsup{\phi}{i}{}\mp@subsup{\prod}{k}{}\mp@subsup{M}{ki}{}\mathrm{ for each }i\in
    end procedure
```

$M_{i, j}:=\operatorname{project}\left(\phi_{i} \prod_{k \neq j} M_{k, i}, S_{i, j}\right)$

