

EECS 592: Bayes Net Example, Mar. 21, 2018

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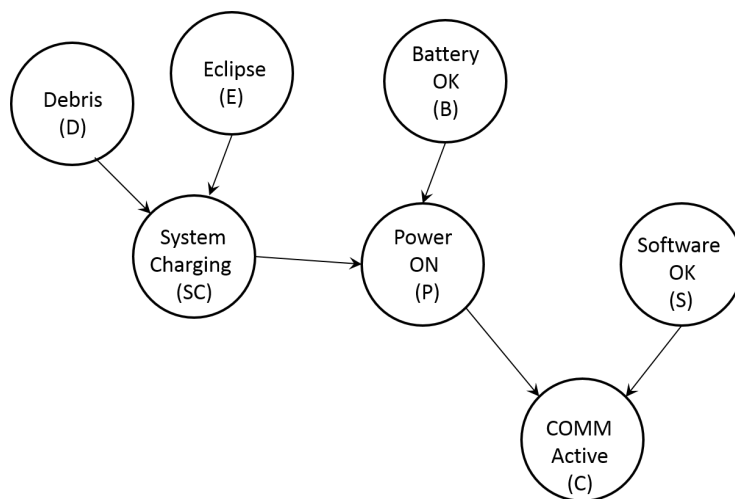


Figure 1: Example Bayesian Network.

Network Probabilities: $P(D) = 0.1$; $P(E) = 0.3$; $P(B) = 0.95$; $P(S) = 0.99$
 $P(SC|D, E) = 0.0$; $P(SC|D, \neg E) = 0.6$; $P(SC|\neg D, E) = 0.0$; $P(SC|\neg D, \neg E) = 0.9$
 $P(P|SC, B) = 0.9$; $P(P|SC, \neg B) = 0.1$; $P(P|\neg SC, B) = 0.7$; $P(P|\neg SC, \neg B) = 0.0$
 $P(C|P, S) = 0.95$; $P(C|P, \neg S) = 0.5$; $P(C|\neg P, S) = 0.01$; $P(C|\neg P, \neg S) = 0.0$

1 Problem 1:

Which node(s) if any are conditionally independent of P given SC and C ?

Ans: Evidence for node SC breaks the connection between P and D, E . Evidence for node C causes P to depend on node S . So, D and E are conditionally independent of P .

2 Problem 2:

Which node(s) if any are conditionally independent of B given SC ?

Ans: Again, evidence for SC breaks the connection between the P side of the network and D, E . Node B is also independent of S because no evidence is given for C . Overall, nodes D , E , and S are conditionally independent of B .

3 Problem 3:

Compute $P(SC|E)$

Ans:

$$P(SC|E) = P(SC|D, E)P(D|E) + P(SC|\neg D, E)P(\neg D|E)$$

Because D and E are parents of P , and no other (downstream) evidence is given in $P(D|E)$, D is conditionally independent of E such that $P(D|E) = P(D)$. A similar answer is given for the negation term. This produces a final answer of:

$$P(SC|E) = P(SC|D, E)P(D) + P(SC|\neg D, E)P(\neg D) = 0.$$

4 Problem 4:

Compute $P(SC|P)$

Ans:

$$P(SC|P) = \frac{P(P|SC)P(SC)}{P(P)}$$

$$\begin{aligned} P(P|SC) &= P(P|SC, B)P(B|SC) + P(P|SC, \neg B)P(\neg B|SC) \\ &= P(P|SC, B)P(B) + P(P|SC, \neg B)P(\neg B) = 0.86 \end{aligned}$$

Above, we also note that B is conditionally independent of SC since B and SC are parent nodes of P , and P plus all other nodes downstream of P are not given as evidence in $P(B|SC)$.

Now compute marginal probabilities $P(SC)$ and $P(P)$. Note that D and E are conditionally independent so $P(D|E) = P(D)$, etc.

$$\begin{aligned} P(SC) &= P(SC|D, E)P(D)P(E) + P(SC|D, \neg E)P(D)P(\neg E) \\ &\quad + P(SC|\neg D, E)P(\neg D)P(E) + P(SC|\neg D, \neg E)P(\neg D)P(\neg E) = 0.609 \end{aligned}$$

Similarly, $P(B|SC) = P(B)$ since B is conditionally independent of B .

$$\begin{aligned} P(P) &= P(P|B, SC)P(B)P(SC) + P(P|B, \neg SC)P(B)P(\neg SC) \\ &\quad + P(P|\neg B, SC)P(\neg B)P(SC) + P(P|\neg B, \neg SC)P(\neg B)P(\neg SC) = 0.784 \end{aligned}$$

Finally:

$$P(SC|P) = \frac{P(P|SC)P(SC)}{P(P)} = \frac{0.86 * 0.609}{0.784} = 0.668$$

5 Problem 5 (from real-time lecture (!)):

Compute $P(P|SC, C)$.

Ans:

Steps to multivariable Bayes Rule application:

$$P(P, SC, C) = P(P|SC, C)P(SC, C) = P(P|C, SC)P(C, SC) = P(C|P, SC)P(P, SC)$$

$$P(P, SC) = P(P|SC)P(SC); P(C, SC) = P(C|SC)P(SC)$$

$$P(P|SC, C) = P(P|C, SC)$$

$$P(P|C, SC) = \frac{P(C|P, SC)P(P, SC)}{P(C, SC)}$$

$$P(P|C, SC) = \frac{P(C|P, SC)P(P|SC)P(SC)}{P(C|SC)P(SC)}$$

$$P(P|SC, C) = P(P|C, SC) = \frac{P(C|P, SC)P(P|SC)}{P(C|SC)}$$

Now compute the three probabilities from this Bayes Rule expression. From Problem 4, we computed

$$P(P|SC) = 0.86$$

To compute $P(C|P, SC)$, note that C is conditionally independent of SC given P :

$$P(C|P, SC) = P(C|P) = P(C|P, S)P(S) + P(C|P, \neg S)P(\neg S) = 0.9455$$

Next,

$$P(C|SC) = P(C|SC, P)P(P|SC) + P(C|SC, \neg P)P(\neg P|SC)$$

In Problem 4, we computed $P(P) = 0.784$ so $P(\neg P) = 1 - 0.784 = 0.216$. Also, $P(C|SC, P) = P(C|P, SC) = 0.9455$, and :

$$P(C|SC, \neg P) = P(C|\neg P) = P(C|\neg P, S)P(S) + P(C|\neg P, \neg S)P(\neg S) = 0.0099$$

$$P(C|SC) = 0.9455 * 0.86 + 0.0099 * (1 - 0.86) = 0.8145$$

Finally,

$$P(P|SC, C) = \frac{(0.9455)(0.86)}{(0.8145)} = 0.9983$$