

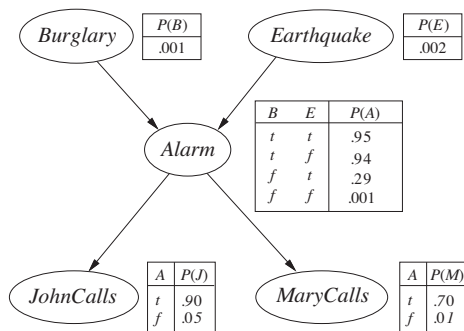
CSC384

Introduction to Artificial Intelligence: Uncertainty

November 13, 2014

Bayesian Networks

Inference

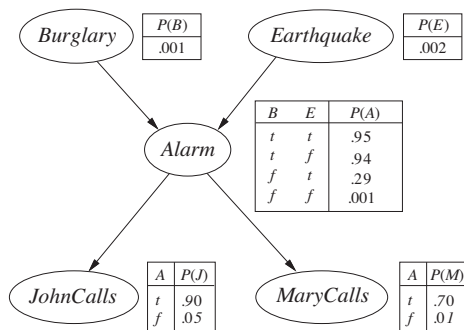


We have: $P(B, E, A, M, J) = P(B) * P(E) * P(A|B, E) * P(M|A) * P(J|A)$

Want to ask a queries in forms such as: $P(B = t|M = f, J = t) = ?$

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Want to ask a queries in forms such as: $P(B = t|M = f, J = t) = ?$

$P(A, B, C, D, E, F, G, H, I, J, K) =$

$P(A) *$

$P(B) *$

$P(C|A) *$

$P(D|A, B) *$

$P(E|C) *$

$P(F|D) *$

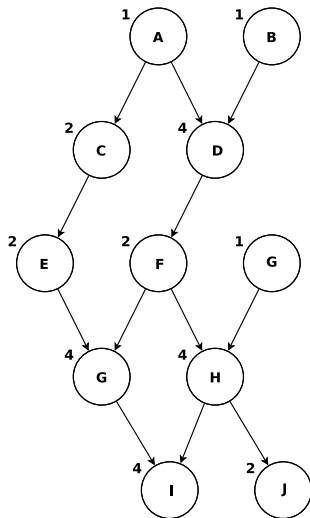
$P(G) *$

$P(H|E, F) *$

$P(I|F, G) *$

$P(J|H, I) *$

$P(K|I)$



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$$P(A, B, C, D, E, F, G, H, I, J, K) = P(A)P(B)P(C|A)P(D|A, B)P(E|C) \\ P(F|D)P(G)P(H|E, F)P(I|F, G)P(J|H, I)P(K|I)$$

We may know that that $H = \text{true}$, $I = \text{False}$. This forms an evidence set. If we want to know $P(D|h, \neg i)$ we can calculate this value by summing out the relevant probabilities.

(Notation: let lower case letters such as a represent $A = t$ and $\neg a$ represent $A = f$)

$$\sum_{A, B, C, E, F, G, J, K} P(A, B, C, d, E, F, G, h, \neg i, J, K) = P(d, h, \neg i)$$

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$$\sum_{A,B,C,E,F,G,J,K} P(A, B, C, d, E, F, G, h, \neg i, J, K) = P(d, h, \neg i) \quad (1)$$

$$\sum_{A,B,C,E,F,G,J,K} P(A, B, C, \neg d, E, F, G, h, \neg i, J, K) = P(\neg d, h, \neg i) \quad (2)$$

$$P(d, h, \neg i) + P(\neg d, h, \neg i) = P(h, \neg i) \quad (3)$$

$$P(d|h, \neg i) = P(d, h, \neg i)/P(h, \neg i) \quad (4)$$

$$P(\neg d|h, \neg i) = P(\neg d, h, \neg i)/P(h, \neg i) \quad (5)$$

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We can use properties of Bayes nets to decompose the earlier summation

$$\sum_{A,B,C,E,F,G,J,K} P(A, B, C, d, E, F, G, h, \neg i, J, K) = P(d, h, \neg i) =$$
$$P(A)P(B)P(C|A)P(d|A, B)P(E|C)P(F|d)P(G)P(h|E, F)$$
$$P(\neg i|F, G)P(J|h, \neg i)P(K|\neg i)$$

Rearrange the summations so that we only sum over relevant variables:

$$\sum_A, \sum_B, \sum_C, \sum_E, \sum_F, \sum_G, \sum_J, \sum_K P(A)P(B)P(C|A)P(d|A, B)P(E|C)$$
$$P(F|d)P(G)P(h|E, F)P(\neg i|F, G)P(J|h, \neg i)P(K|\neg i)$$

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$$\begin{aligned} & \sum_A, \sum_B, \sum_C, \sum_E, \sum_F, \sum_G, \sum_J, \sum_K P(A)P(B)P(C|A)P(d|A, B)P(E|C) \\ & P(F|d)P(G)P(h|E, F)P(\neg i|F, G)P(J|h, \neg i)P(K|\neg i) = \\ & \sum_A P(A), \sum_B P(B), \sum_C P(C|A)P(d|A, B), \sum_E P(E|C), \\ & \sum_F P(F|d), \sum_G P(G)P(h|E, F)P(\neg i|F, G), \sum_J P(J|h, \neg i), \sum_K P(K|\neg i) = \\ & \sum_A P(A), \sum_B P(B)P(d|A, B), \sum_C P(C|A), \sum_E P(E|C), \\ & \sum_F P(F|d)P(h|E, F), \sum_G P(G)P(\neg i|F, G), \sum_J P(J|h, \neg i), \sum_K P(K|\neg i) \end{aligned}$$

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$$\sum_A P(A), \sum_B P(B)P(d|A, B), \sum_C P(C|A), \sum_E P(E|C),$$
$$\sum_F P(F|d)P(h|E, F), \sum_G P(G)P(\neg i|F, G), \sum_J P(J|h, \neg i), \sum_K P(K|\neg i)$$

Given the above note that:

$$\sum_K P(K|\neg i) = P(k|\neg i) + Pr(\neg k|\neg i) = c_1$$
$$\sum_J P(J|h, \neg i)c_1 = c_1 \sum_J P(J|h, \neg i) = c_1(P(j|h, \neg i) + P(\neg j|h, \neg i)) = c_1c_2$$

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$$\sum_K P(K|\neg i) = P(k|\neg i) + P(\neg k|\neg i) = c_1$$

$$\sum_J P(J|h, \neg i)c_1 = c_1 \sum_J P(J|h, \neg i) = c_1(P(j|h, \neg i) + P(\neg j|h, \neg i)) = c_1 c_2$$

$$c_1 c_2 \sum_G P(G)P(\neg i|F, G) = c_1 c_2(P(g)P(\neg i|F, g) + P(\neg g)P(\neg i|F, \neg g))$$

$P(\neg i|F, g)$ depends on F and is not a single number!

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Coming from the other direction:

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Expanding in variable order will result in exponential increases in the size of the equation, but many repeated subterms

$$\begin{aligned} & P(a) \left(\sum_B P(B)P(d|a, B), \sum_C P(C|a), \sum_E P(E|C), \right. \\ & \left. \sum_F P(F|d)P(h|E, F), \sum_G P(G)P(\neg i|F, G), \sum_J P(J|h, \neg i), \sum_K P(K|\neg i) \right) + \\ & P(\neg a) \left(\sum_B P(B)P(d|\neg a, B), \sum_C P(C|\neg a), \sum_E P(E|C), \right. \\ & \left. \sum_F P(F|d)P(h|E, F), \sum_G P(G)P(\neg i|F, G), \sum_J P(J|h, \neg i), \sum_K P(K|\neg i) \right) = \\ & P(a)P(b)p(d|a, b)f_1 + P(\neg a)P(b)p(d|\neg a, b)f_2 + \\ & P(a)P(\neg b)p(d|a, \neg b)f_1 + P(\neg a)P(\neg b)p(d|\neg a, \neg b)f_2 \end{aligned}$$

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Dynamic Programming

- Store values of computed subterms for reuse
- Can in some cases result in an exponential reduction in the amount of calculation necessary!
- Common algorithm for doing this: Variable elimination

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$$\sum_A P(A), \sum_B P(B)P(d|A, B), \sum_C P(C|A), \sum_E P(E|C), \\ \sum_F P(F|d)P(h|E, F), \sum_G P(G)P(\neg i|F, G), \sum_J P(J|h, \neg i), \sum_K P(K|\neg i)$$

Note that in this equation

$$\sum_K P(K|\neg i) = 1 \\ \sum_J P(J|h, \neg i) = 1$$

And we can therefore remove these terms from the original equation (Why is this true?)

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Variable Elimination

We approach variable elimination from the inside out as with the first approach we took.

$$\sum_K P(K|\neg i) = P(k|\neg i) + P(\neg k|\neg i) = 1$$

$$\sum_J P(J|h, \neg i)c_1 = c_1 \sum_J P(J|h, \neg i) = c_1(P(j|h, \neg i) + P(\neg j|h, \neg i)) = 1$$

$$\sum_G P(G)P(\neg i|F, G) = P(g)P(\neg i|F, g) + P(\neg g)P(\neg i|F, \neg g)$$

We continue by computing two different numbers for $P(\neg i|F, g)$, one for each value of F

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Variable Elimination

$$t(f) = \sum_G P(G)P(\neg i|f, G)$$

$$t(\neg f) = \sum_G P(G)P(\neg i|\neg f, G)$$

$$t(f) = P(g)P(\neg i|f, g) + P(\neg g)P(\neg i|f, \neg g)$$

$$t(\neg f) = P(g)P(\neg i|\neg f, g) + P(\neg g)P(\neg i|\neg f, \neg g)$$

We can use this to sum out F

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Variable Elimination

$$\begin{aligned} \sum_F P(F|d)P(h|E, F), \sum_G P(G)P(\neg i|F, G) &= \\ P(f|d)P(h|E, f), \sum_G P(G)P(\neg i|f, G) + & \\ P(\neg f|d)P(h|E, \neg f), \sum_G P(G)P(\neg i|\neg f, G) & \\ &= \\ P(f|d)P(h|E, f)t(f) + P(\neg f|d)P(h|E, \neg f)t(\neg f) &= \\ \sum_F P(F|d)P(h|E, F)t(F) &= \end{aligned}$$

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Variable Elimination

- At each stage we compute a table of values with entries for every instantiation of variables in the sum
- Table size is exponential in the number of variables
- The tables are called *Factors*
- $f(X, Y)$ denotes a factor with variable sets X and Y