CS221 car

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Problem 1

(a) $P(C_2 = 1|D_2 = 0) = \frac{P(D_2=0|C_2=1)P(C_2=1)}{P(D_2=0)} = \frac{P(D_2=0|C_2=1)P(C_2=1)}{P(D_2=0,C_2=1)+P(D_2=0,C_2=0)} = \frac{\eta(0.5\epsilon+0.5(1-\epsilon))}{0.5\eta+0.5(1-\eta)}$

$= \eta$

(b) $P(C_2|D_2 = 0, D_3 = 1) \propto [p(c_1)p(c_2 = 0|c_1 = 1) + p(c_1)p(c_2 = 0|c_1 = 0)]$
$[p(c_3 = 1|c_2 = 0)p(D_3 = 1|C_3 = 1) + p(c_3 = 0|c_2 = 0)]p(d_3 = 1|c_3 = 0)p(D_3 = 0|c_2 = 0)$

$P(C_2|D_2 = 0, D_3 = 1) = \frac{\eta(\eta\epsilon+(1-\eta)(1-\epsilon))}{\eta(\eta\epsilon+(1-\eta)(1-\epsilon))+(\eta(1-\epsilon)+(1-\eta)\epsilon)(1-\eta)}$

(c) (a) $P(C_2 = 1|D_2 = 0) = \eta = 0.2$ $P(C_2|D_2 = 0, D_3 = 1) = \frac{0.148}{0.148+0.208} = 0.4157$

(b) Adding the sensor increased the probability of it being at position 1 because we are not expecting the car to move so the sensor reading at position one means the car is more likely to be there

(c) setting $P(C_2|D_2 = 0, D_3 = 1) = P(C_2 = 1|D_2 = 0)$ we have
$0.2 = \frac{0.2(0.2\epsilon+(1-0.2)(1-\epsilon))}{0.2(0.2\epsilon+(1-0.2)(1-\epsilon))+(0.2(1-\epsilon)+(1-0.2)\epsilon)(1-0.2)}$ solving that gives $\epsilon = 0.5$

Problem5

(a) $P(C_{11} = c_{11}, C_{12} = c_{12}|E_1 = e_1) \propto$
$(p(c_{11})p(c_{12}))\ p_\nu(e_{11}; \|a_1 - c_{11}\|, \sigma^2)p_\nu(e_{12}; \|a_1 - c_{12}\|, \sigma^2) +$
$(p(c_{11})p(c_{12}))\ p_\nu(e_{11}; \|a_1 - c_{12}\|, \sigma^2)p_\nu(e_{12}; \|a_1 - c_{11}\|, \sigma^2)$

(b) For any two elements in the optimal assignment we can substitute these two cars assignments we would get the same result from the probability above because the prior belief is the same for both this means that we can permute the assignment in any order we want because there are K! total permutations we get the K! number of assignments.

(c) We end up with tree width K
this is because when we generate the factor graph then run variable elimination we will

have a minmax arity of K when removing the latest sensor variable then the latest car variables becasue the sensor varibales have K factors one from each car.