

Tutorial 8 - Belief Propagation and Sampling

COMP9418 – Advanced Topics in Statistical Machine Learning

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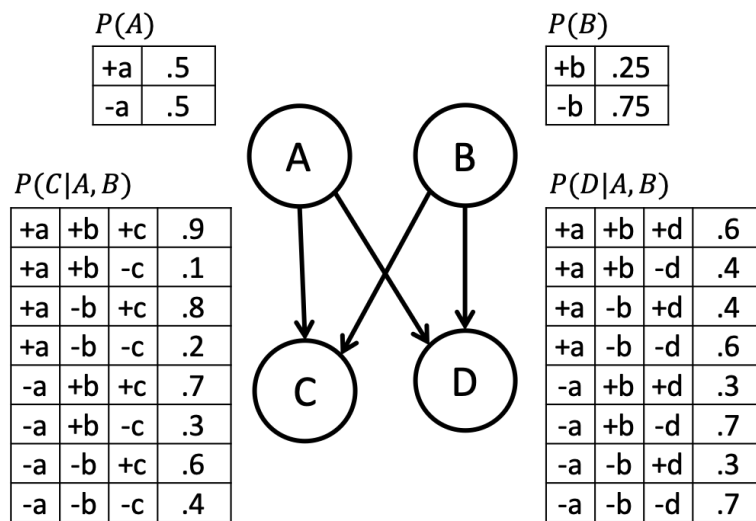
Lecture: Belief Propagation and Sampling

Topic: Questions from lecture topics

Last revision: Monday 16th November, 2020 at 15:34

Question 1

Consider the following Bayesian network:



Suppose we condition on evidence $e : D = \text{true}$. Suppose that we have run the Parallel Iterative Belief Propagation (IBP) algorithm on the network, where it converges and yields the following set of messages and family marginals:

A	$\pi_C(A)$	$\pi_D(A)$	$\lambda_C(A)$	$\lambda_D(A)$
+a		.5	.5	.6
-a		.5	.5	.4

B	$\pi_C(B)$	$\pi_D(B)$	$\lambda_C(B)$	$\lambda_D(B)$
+b	.3	.25	.5	
-b	.7	.75	.5	

A	B	C	$\beta(A, B, C)$
+a	+b	+c	.162
+a	+b	-c	.018
+a	-b	+c	
+a	-b	-c	.084
-a	+b	+c	.084
-a	+b	-c	.036
-a	-b	+c	.168
-a	-b	-c	.112

A	B	D	$\beta(A, B, D)$
+a	+b	+d	.2
+a	+b	-d	0
+a	-b	+d	
+a	-b	-d	0
-a	+b	+d	.1
-a	+b	-d	0
-a	-b	+d	.3
-a	-b	-d	0

- Fill in the missing values for IBP messages.
- Fill in the missing values for family marginals.
- Compute marginals $\beta(A)$ and $\beta(B)$ using the IBP messages and those computed in (a).
- Compute marginals $\beta(A)$ and $\beta(B)$ by summing out the appropriate variables from the family marginals $\beta(ABC)$ as well as $\beta(ABD)$.
- Compute joint marginal $\beta(AB)$ by summing out the appropriate variables from family marginals $\beta(ABC)$ as well as $\beta(ABD)$.
- Are the marginals computed in (d) consistent? What about those computed in (e)?

Consider the following IBP algorithm:

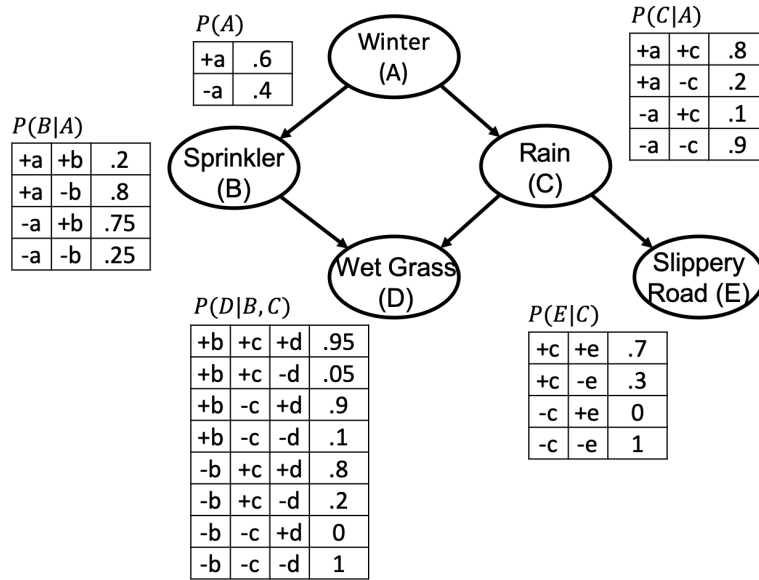
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Data:  $N$ : Bayesian network
Data:  $\mathbf{e}$ : evidence
Result: Approximate marginals,  $\beta(X\mathbf{U})$  of  $P(X\mathbf{U}|\mathbf{e})$  for each family  $X\mathbf{U}$  in  $N$ 
1 begin
2    $t \leftarrow 0$ ;
3   initialize all messages;
4   while messages have not converged do
5      $t \leftarrow t + 1$ ;
6     for each node  $X$  with parents  $\mathbf{U}$  do
7       for each parent  $U_i$  do
8          $\lambda_X^t(U_i) = \eta \sum_{X\mathbf{U} \setminus \{U_i\}} \lambda_{\mathbf{e}}(X) \phi_X(X, \mathbf{U}) \prod_{k \neq i} \pi_X^{t-1}(U_k) \prod_j \lambda_{Y_j}^{t-1}(X)$ ;
9       end
10      for each child  $Y_j$  do
11         $\pi_{Y_j}^t(X) = \eta \sum_{\mathbf{U}} \lambda_{\mathbf{e}}(X) \phi_X(X, \mathbf{U}) \prod_i \pi_X^{t-1}(U_i) \prod_{k \neq j} \lambda_{Y_k}^{t-1}(X)$ ;
12      end
13    end
14  end
15 end
16 return  $\beta(X\mathbf{U}) = \eta \lambda_{\mathbf{e}}(X) \phi_X(X, \mathbf{U}) \prod_i \pi_X^t(U_i) \prod_j \lambda_{Y_j}^t(X)$ 

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Question 2

Consider the following Bayesian network:



and the parameter θ_a representing the probability of $A = \text{false}$ (i.e., it is not winter). For each of the following values of this parameter, 0.01, 0.4 and 0.99 do the following:

- Compute the probability of $P(+d, +e)$: wet grass and slippery road. You can use the code from previous tutorials.
- Estimate $P(+d, +e)$ using forward sampling with sample sizes ranging from $n = 100$ to $n = 15,000$.
- Generate a plot with n on the x -axis and the exact value of $P(+d, +e)$ and the estimate for $P(+d, +e)$ on the y -axis.
- Generate a plot with n on the x -axis and the exact variance of the estimate for $P(+d, +e)$ and the sample variance on the y -axis.