Variable Elimination: Basic Ideas

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Topics

- 1. Types of Inference Algorithms
- 2. Variable Elimination: the Basic ideas
- 3. Variable Elimination
 - Sum-Product VE Algorithm
 - Sum-Product VE for Conditional Probabilities
- 4. Variable Ordering for VE

Inference Algorithms

- Types of inference algorithms
 - 1. Exact
 - 1. Variable Elimination
 - 2. Clique trees (Belief Propagation)

2. Approximate

- 1. Optimization
 - 1. Propagation with approximate messages
 - 2. Variational (analytical approximations)
- 2. Particle-based (sampling)

Variable Elimination: Basic Ideas

- We begin with principles underlying exact inference in PGMs
- As we show, the same BN structure that allows compaction of complex distributions also helps support inference
- In particular we can use dynamic programming techniques to perform inference even for large and complex networks in reasonable time

Intuition for Variable Elimination

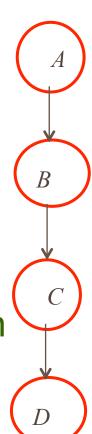
- Consider inference is a very simple BN
 A →B →C →D
 - E.g., sequence of words
 - CPDs are first order word probabilities
- We consider phased computation
 - Probabilities of four words: The, quick, brown, fox
 - Use results of a previous phase in computation of next phase
 - Then reformulate this process in terms of a global computation on the joint distribution

Exact Inference: Variable Elimination

- To compute P(B),
 - i.e., distribution of values b of B, we have

$$P(B) = \sum_{a} P(A, B) = \sum_{a} P(a)P(B \mid a)$$

- required P(a), P(b|a) available in BN
- If A has k values and B has m values
 - For each b: k multiplications and k-1 addition
 - Since there are m values of B, process is repeated for each value of b:
 - this computation is $O(k \times m)$



Moving Down BN

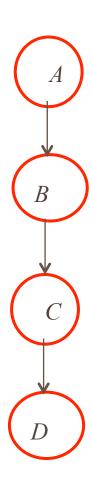
- Assume we want to compute P(C)
- Using same analysis

$$P(C) = \sum_{b} P(B, C) = \sum_{b} P(b)P(C \mid b)$$

- -P(c|b) is given in CPD b
- But P(B) is not given as network parameters
- It can be computed using

$$P(B) = \sum_{a} P(A, B) = \sum_{a} P(a)P(B \mid a)$$



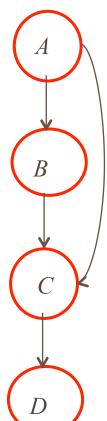


Computation depends on Structure

- 1. Structure of BN is critical for computation
 - If A had been a parent of C

$$P(C) = \sum_{i} P(b)P(C \mid b)$$

- would not have sufficed
- 2. Algorithm does not compute single values but sets of values at a time
 - -P(B) over all possible values of B are used to compute P(C)

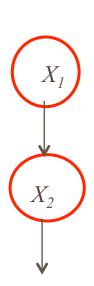


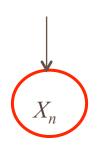
Complexity of General Chain

- In general, if we have $X_1 \rightarrow X_2 \rightarrow \dots \rightarrow X_n$
- and there are k values of X_i , total cost is $O(nk^2)$



- Generate entire joint and summing it out
- Would generate k^n probabilities for the events $x_1, \dots x_n$
- In this example, despite exponential size of joint distribution we can do inference in linear time





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Insight that avoids exponentiality(

The joint probability decomposes as

$$P(A,B,C,D)=P(A)P(B|A)P(C|B)P(D|C)$$

- To compute P(D) we need to sum together all entries where $D=d^{l}$
 - And separately entries where $D=d^2$

- Examine summation

 - $P(c^l|b^l)P(d^l|c^l)$
 - Modify to first compute
 - $P(a^1)P(b^1|a^1)+P(a^2)P(b^1|a^2)$
 - then multiply by common term

$$P(a^1)$$
 $P(b^1 | a^1)$ $P(c^1 | b^1)$ $P(d^2 | c^1)$
+ $P(a^2)$ $P(b^1 | a^2)$ $P(c^1 | b^1)$ $P(d^2 | c^1)$

 $P(c^2 | b^1)$

$$+ P(a^{1}) P(b^{1} | a^{1}) P(c^{2} | b^{1}) P(d^{2} | c^{2})$$

First Transformation of sum

- Same structure is repeated throughout table
- Performing the same transformation we get the summation for P(D) as

```
\begin{array}{c} (P(a^{1})P(b^{1}\mid a^{1}) + P(a^{2})P(b^{1}\mid a^{2})) & P(c^{1}\mid b^{1}) & P(d^{1}\mid c^{1}) \\ + & (P(a^{1})P(b^{2}\mid a^{1}) + P(a^{2})P(b^{2}\mid a^{2})) & P(c^{1}\mid b^{2}) & P(d^{1}\mid c^{1}) \\ + & (P(a^{1})P(b^{1}\mid a^{1}) + P(a^{2})P(b^{1}\mid a^{2})) & P(c^{2}\mid b^{1}) & P(d^{1}\mid c^{2}) \\ + & (P(a^{1})P(b^{2}\mid a^{1}) + P(a^{2})P(b^{2}\mid a^{2})) & P(c^{2}\mid b^{1}) & P(d^{1}\mid c^{2}) \\ + & (P(a^{1})P(b^{1}\mid a^{1}) + P(a^{2})P(b^{1}\mid a^{2})) & P(c^{1}\mid b^{1}) & P(d^{2}\mid c^{1}) \\ + & (P(a^{1})P(b^{2}\mid a^{1}) + P(a^{2})P(b^{2}\mid a^{2})) & P(c^{1}\mid b^{2}) & P(d^{2}\mid c^{1}) \\ + & (P(a^{1})P(b^{1}\mid a^{1}) + P(a^{2})P(b^{1}\mid a^{2})) & P(c^{2}\mid b^{1}) & P(d^{2}\mid c^{2}) \\ + & (P(a^{1})P(b^{2}\mid a^{1}) + P(a^{2})P(b^{2}\mid a^{2})) & P(c^{2}\mid b^{2}) & P(d^{2}\mid c^{2}) \end{array}
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- Observe certain terms are repeated several times in this expression
- $P(a^{1})P(b^{1}|a^{1})+P(a^{2})P(b^{1}|a^{2})$ and
- $P(a^1)P(b^2|a^1)+P(a^2)P(b^2|a^2)$ are repeated four times

2nd & 3rd transformation on the sum

- Defining τ_I : $Val(B) \rightarrow R$
 - where $\tau_1(b^1)$ and $\tau_1(b^2)$ are the two expressions, we get

- Can reverse the order of a sum and product
 - sum first, product next

$$(\tau_{1}(b^{1})P(c^{1} \mid b^{1}) + \tau_{1}(b^{2})P(c^{1} \mid b^{2})) \quad P(d^{1} \mid c^{1})$$

$$+ (\tau_{1}(b^{1})P(c^{2} \mid b^{1}) + \tau_{1}(b^{2})P(c^{2} \mid b^{2})) \quad P(d^{1} \mid c^{2})$$

$$(\tau_{1}(b^{1})P(c^{1} \mid b^{1}) + \tau_{1}(b^{2})P(c^{1} \mid b^{2})) \quad P(d^{2} \mid c^{1})$$

$$+ (\tau_{1}(b^{1})P(c^{2} \mid b^{1}) + \tau_{1}(b^{2})P(c^{2} \mid b^{2})) \quad P(d^{2} \mid c^{2})$$

$$12$$

Fourth Transformation of sum

- Again notice shared expressions that are better computed once and used multiple times
 - − We define τ_2 : $Val(C) \rightarrow R$

$$\tau_{2}(c^{1}) = \tau_{1}(b^{1})P(c^{1}|b^{1}) + \tau_{1}(b^{2})P(c^{1}|b^{2})$$
$$\tau_{2}(c^{2}) = \tau_{1}(b^{1})P(c^{2}|b^{1}) + \tau_{1}(b^{2})P(c^{2}|b^{2})$$

$$au_2(c^1) ext{ } P(d^2 \mid c^1) \\ + au_2(c^2) ext{ } P(d^2 \mid c^2) ext{ }$$

Summary of computation

- We begin by computing $\tau_1(B)$
- Requires 4 multiplications and 2 additions
- Using it we can compute τ₂(C) which also requires 4 multis and 2 adds
- Finally we compute P(D) at same cost
- Total no of ops is 18
- Joint distribution requires 16 x 3=48 mps and 14 adds

Computation Summary

Transformation we have performed has steps

$$P(D) = \sum_{C} \sum_{B} \sum_{A} P(A) P(B \mid A) P(C \mid B) P(D \mid C)$$

We push the first summation resulting in

$$P(D) = \sum_{C} P(D \mid C) \sum_{B} P(C \mid B) \sum_{A} P(A) P(B \mid A)$$

- We compute the product $\psi_I(A,B) = P(A)P(B|A)$ and sum out A to obtain the function $\tau_1(B) = \sum_i \psi_1(A,B)$
 - For each value of b, we compute

$$\tau_{1}(b) = \sum_{A} \psi_{1}(A, b) = \sum_{A} P(A)P(b \mid A)$$
$$\psi_{2}(B, C) = \tau_{1}(B)P(C \mid B)$$

- We then continue $\tau_2(C) = \sum_{B} \psi_2(B,C)$
 - Resulting $\tau_2(C)$ is used to compute P(D)

Computation is Dynamic Programming

• Naiive way for $P(D) = \sum_{C} \sum_{B} \sum_{A} P(A)P(B \mid A)P(C \mid B)P(D \mid C)$ would have us compute every

$$P(b) = \sum_{A} P(A)P(b \mid A)$$

- many times, once for every value of C and D
- For a chain of length n this would be computed exponentially many times
- Dynamic Programming inverts order of computation— performing it inside out rather than outside in
 - First computing once for all values in $\tau_1(B)$, that allows us to compute $\tau_2(C)$ once for all, etc.

Ideas that prevented exponential blowup

- Because of structure of BN, some subexpressions depend only on a small no. of variables
- By computing and caching these results we can avoid generating them exponential no. of times