

Inference

Variable Elimination

# Graph-Based Perspective

### Initial Graph

#### $\phi_J(J,L,S)\phi_L(L,G)\phi_S(S,I)\phi_G(G,I,D)\phi_H(H,G,J)\phi_I(I)\phi_D(C,D)\phi_C(C)$



 $\phi_J(J,L,S)\phi_L(L,G)\phi_S(S,I)\phi_G(G,I,D)\phi_H(H,G,J)\phi_I(I)\phi_D(C,D)\phi_C(C)$ 

• Eliminate: C

 $\underline{\tau_1(D)} = \sum_C \phi_C(C)\phi_D(C,D)$ 



Induced Markov network for the current set of factors

 $\phi_J(J,L,S)\phi_L(L,G)\phi_S(S,I)\phi_G(G,I,D)\phi_H(H,G,J)\phi_I(I)\tau_1(D)$ 

• Eliminate: D

$$\tau_2(G,I) = \sum_D \phi_G(G,I,D)\tau_1(D)$$

Induced Markov network for the current set of factors



 $\phi_J(J,L,S)\phi_L(L,G)\phi_S(S,I)\phi_I(I)\phi_H(H,G,J)\tau_2(G,I)$ 

• Eliminate: I

$$\tau_3(S,G) = \sum_I \phi_S(S,I)\phi_I(I)\tau_2(G,I)$$
  
all variables connected to I become  
-connected directly



Induced Markov network for the current set of factors

 $\phi_J(J,L,S)\phi_L(L,G)\phi_H(H,G,J)\tau_3(S,G)$ 

• Eliminate: H

$$\tau_4(G,J) = \sum_H \phi_H(H,G,J)$$



Induced Markov network for the current set of factors

 $\phi_J(J,L,S)\phi_L(L,G)\tau_3(S,G)\tau_4(G,J)$ 

• Eliminate: G



$$\tau_5(L,J) = \sum_G \phi_L(L,G) \tau_3(S,G) \tau_4(G,J)$$

Induced Markov network for the current set of factors

 $\phi_J(J,L,S)\tau_5(L,J)$ 

• Eliminate: L,S



Induced Markov network for the current set of factors

 $\phi_J(J,L,S)\tau_5(L,J)$ 

• Eliminate: L,S



Induced Markov network for the current set of factors

### Induced Graph

- The induced graph  $I_{\Phi,\alpha}$  over factors  $\Phi$  and ordering  $\alpha$ :
  - Undirected graph
  - $-X_i$  and  $X_j$  are connected if they appeared in the same factor in a run of the VE algorithm using  $\alpha$  as the ordering



## Cliques in the Induced Graph

• Theorem: Every factor produced during VE is a clique in the induced graph

$$\begin{split} \tau_{1}(D) &= \sum_{C} \phi_{C}(C) \phi_{D}(C, D) \\ \tau_{2}(G, I) &= \sum_{D} \phi_{G}(G, I, D) \tau_{1}(D) \\ \tau_{3}(S, G) &= \sum_{I} \phi_{S}(S, I) \phi_{I}(I) \tau_{2}(G, I) \\ \tau_{4}(G, J) &= \sum_{H} \phi_{H}(H, G, J) \\ \tau_{5}(L, J) &= \sum_{G} \phi_{L}(L, G) \tau_{3}(S, G) \tau_{4}(G, J) \\ \tau_{6} &= \sum_{L,S} \phi_{J}(J, L, S) \tau_{5}(L, J) \end{split}$$



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### Cliques in the Induced Graph

• Theorem: Every (maximal) clique in the induced graph is a factor produced during VE

$$\begin{split} \tau_1(D) &= \sum_C \phi_C(C) \phi_D(C,D) \\ \tau_2(G,I) &= \sum_D \phi_G(G,I,D) \tau_1(D) \\ \tau_3(S,G) &= \sum_T \phi_S(S,I) \phi_I(I) \tau_2(G,I) \\ \tau_4(G,J) &= \sum_H \phi_H(H,G,J) \\ \tau_5(L,J) &= \sum_G \phi_L(L,G) \tau_3(S,G) \tau_4(G,J) \\ \tau_6 &= \sum_{L,S} \phi_J(J,L,S) \tau_5(L,J) \end{split}$$





### Cliques in the Induced Graph

• Theorem: Every (maximal) clique in the induced graph is a factor produced during VE

Consider a max clique -Some variable is first to be eliminated D once a variable is eliminated - no new neighborg are added to it ) when eliminated it alree dy had all the clique members as neighbors ) penticipated in factor with all there other variables ) when multiplied together, we have a factor over all of them H

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### Induced Width

- The width of an induced graph is the number of nodes in the largest clique in the graph minus 1
- <u>Minimal induced width</u> of a graph K is  $min_{\alpha}(width(I_{K,\alpha}))$
- Provides a lower bound on best performance of VE to a model factorizing over K

### Summary

- Variable elimination can be viewed as transformations on undirected graph
  - Elimination connects all node's current
    neighbors
- <u>Cliques</u> in resulting <u>induced</u> graph directly correspond to algorithm's complexity