

# Propagation in Bayesian Network

## Real World Applications

# Propagation in Clique Trees

## Main Idea

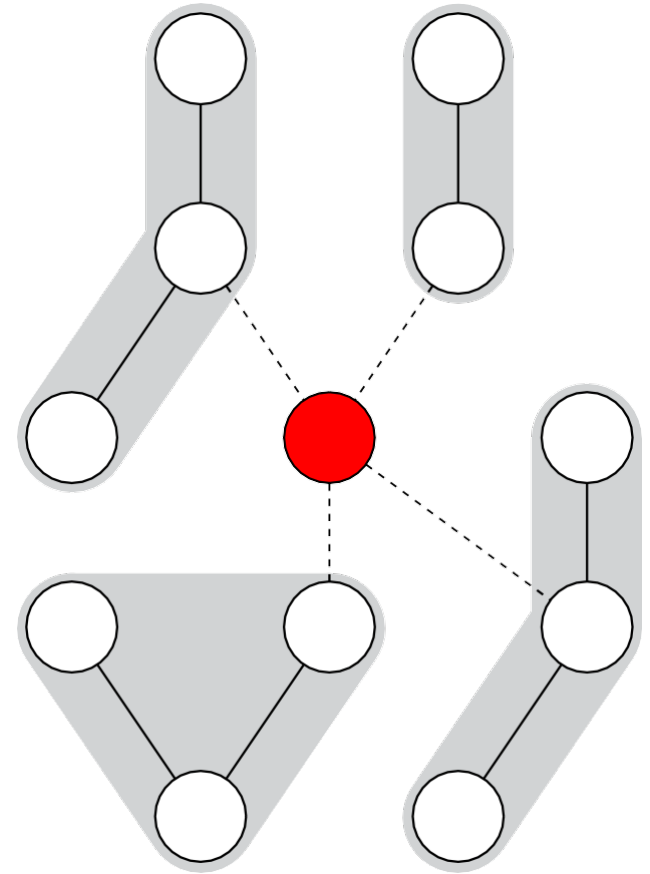
Incorporate evidence into the clique potentials.

Since we are dealing with a tree structure, exploit the fact that a clique “separates” all its neighboring cliques (and their respective subtrees) from each other.

Apply a message passing scheme to inform neighboring cliques about evidence.

Since we do not have edge directions, we will only need one type of message.

After having updated all cliques’ potentials, we marginalize (and normalize) to get the probabilities of single attributes.



# Potential Functions

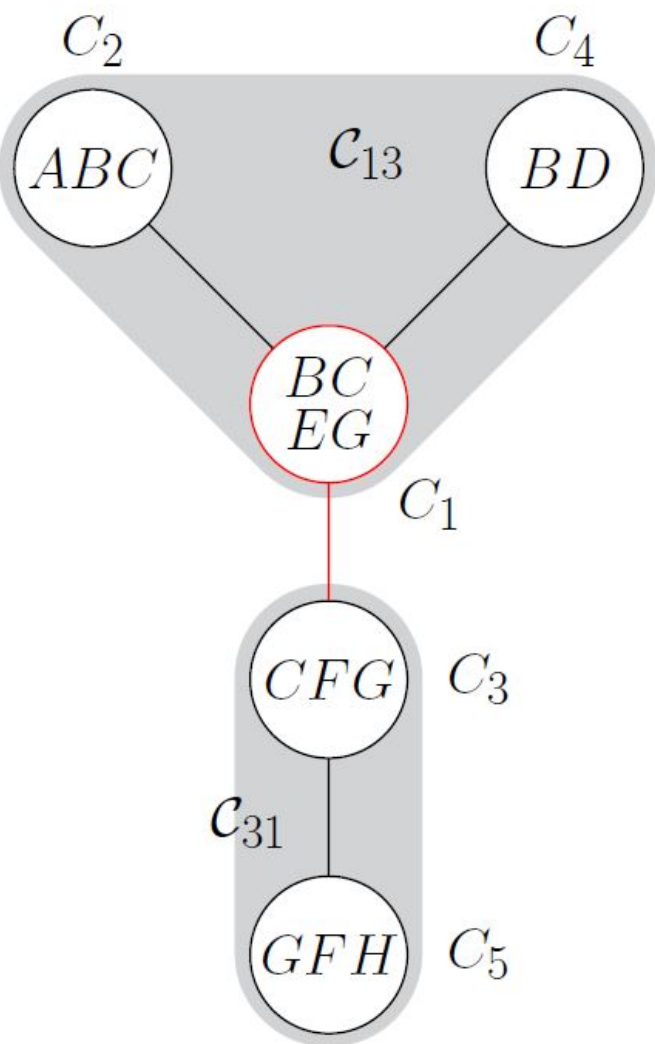
Every clique  $C_i$  maintains a potential function  $\psi_i$ .

If for an attribute  $E$  some evidence  $e$  becomes known, we alter all potential functions of cliques containing  $E$  as follows:

$$\psi_i^*(c_i) = \begin{cases} 0, & \text{if a value in } c_i \text{ is inconsistent with } e \\ \psi_i(c_i), & \text{otherwise} \end{cases}$$

All other potential functions are unchanged.

# Notations



In general:

Clique  $C_i$  has  $q$  neighboring cliques  $B_1, \dots, B_q$ .

$\mathcal{C}_{ij}$  is the set of cliques in the subtree containing  $C_i$  after dropping the link to  $B_j$ .

$X_{ij}$  is the set of attributes in the cliques of  $\mathcal{C}_{ij}$ .

$V = X_{ij} \cup X_{ji}$  (complementary sets)

$S_{ij} = S_{ji} = C_i \cap C_j$  (Separator sets)

$R_{ij} = X_{ij} \setminus S_{ij}$  (Residual sets)

Here:

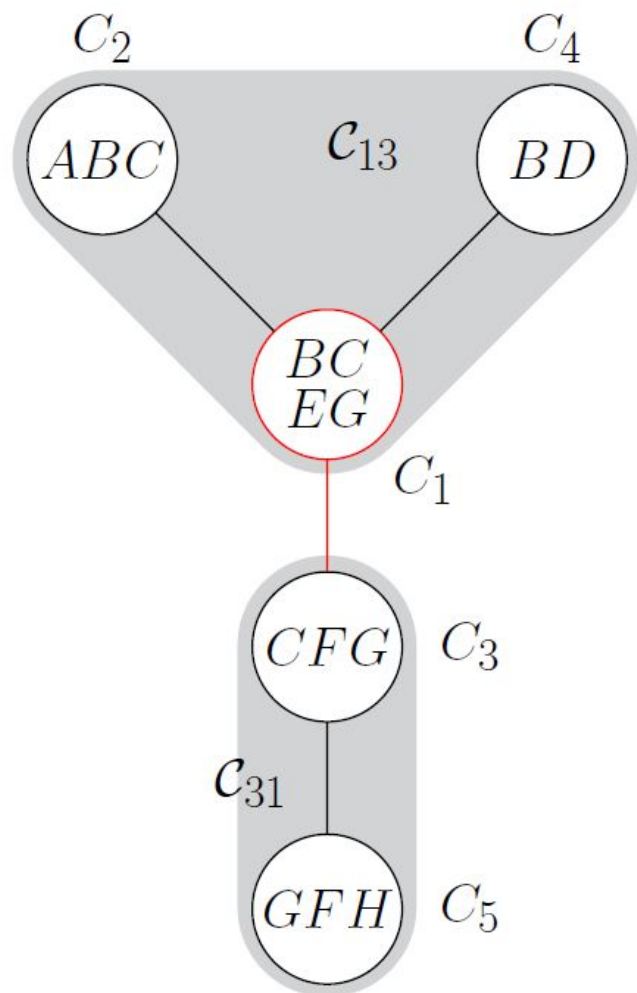
Neighbors of  $C_1$ :  $\{C_2, C_4, C_3\}$ ,  $\mathcal{C}_{13} = \{C_1, C_2, C_4\}$

$X_{13} = \{A, B, C, D, E, G\}$ ,  $S_{13} = \{C, G\}$

$V = X_{13} \cup X_{31} = \{A, B, C, D, E, F, G, H\}$

$R_{13} = \{A, B, D, E\}$ ,  $R_{31} = \{F, H\}$

# Separator Potentials



**Task:** Calculate  $P(s_{ij})$ :

In general:

$$\begin{aligned}V \setminus S_{ij} &= (X_{ij} \cup X_{ji}) \setminus S_{ij} \\ &= (X_{ij} \setminus S_{ij}) \cup (X_{ji} \setminus S_{ij}) \\ &= R_{ij} \cup R_{ji}\end{aligned}$$

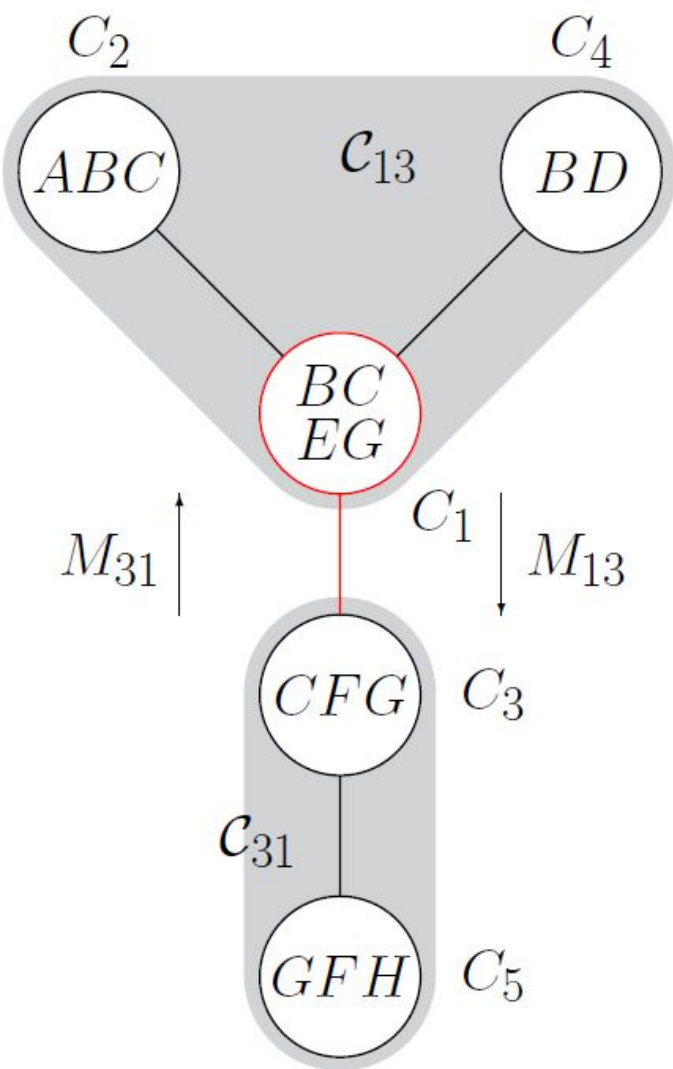
Here:

$$\begin{aligned}V \setminus S_{13} &= (X_{13} \cup X_{31}) \setminus S_{13} \\ &= R_{13} \cup R_{31}\end{aligned}$$

$$\begin{aligned}V \setminus \{C, G\} &= \{A, B, D, E\} \cup \{F, H\} \\ &= \{A, B, D, E, F, H\}\end{aligned}$$

Note:  $R_{ij}$  is the set of attributes that are in  $C_i$ 's subtree but not in  $B_j$ 's. Therefore,  $R_{ij}$  and  $R_{ji}$  are always **disjoint**.

# Separator Potentials



**Task:** Calculate  $P(s_{ij})$ :

In general:

$$P(s_{ij}) = \sum_{v \setminus s_{ij}} \prod_{k=1}^m \psi_k(c_k)$$

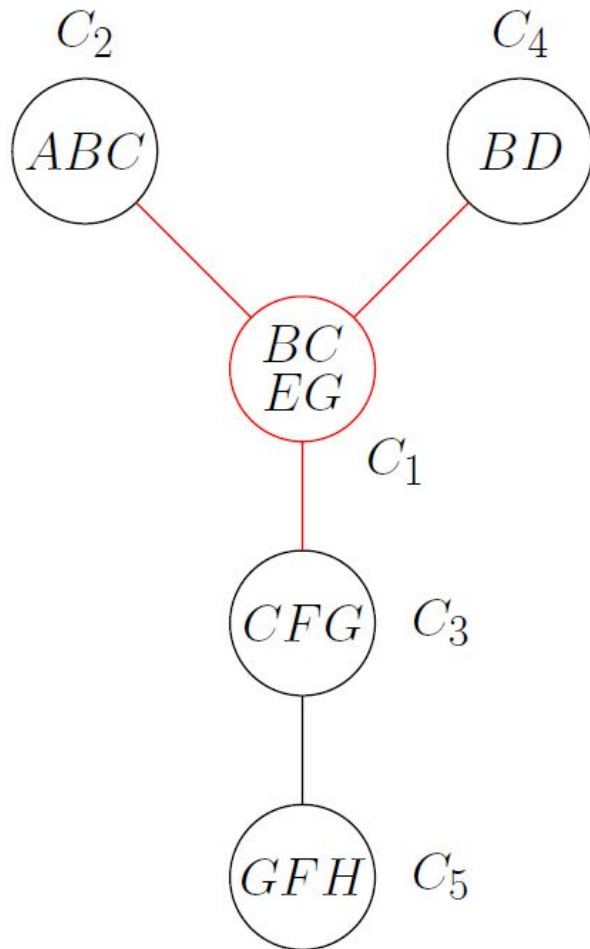
$$\stackrel{\text{last slide}}{=} \sum_{r_{ij} \cup r_{ji}} \prod_{k=1}^m \psi_k(c_k)$$

$$\stackrel{\text{sum rule}}{=} \left( \sum_{r_{ij}} \prod_{c_k \in C_{ij}} \psi_k(c_k) \right) \cdot \left( \sum_{r_{ji}} \prod_{c_k \in C_{ji}} \psi_k(c_k) \right)$$

$$= M_{ij}(s_{ij}) \cdot M_{ji}(s_{ij})$$

$M_{ij}$  is the message sent from  $C_i$  to neighbor  $B_j$  and vice versa.

# Propagation



**Task:** Calculate  $P(c_i)$ :

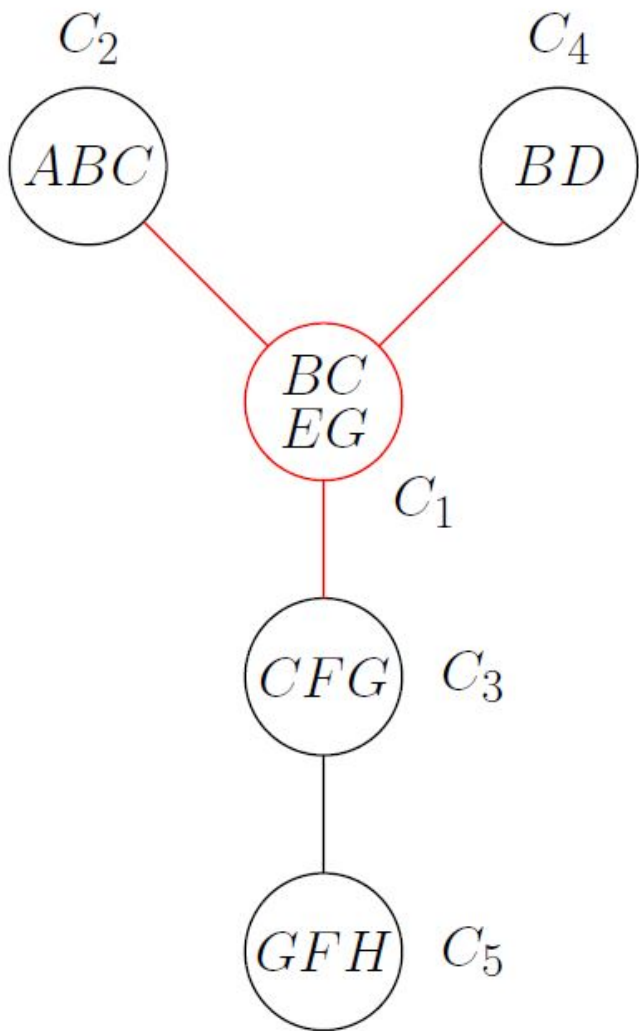
In general:

$$\begin{aligned} V \setminus C_i &= \left( \bigcup_{k=1}^q X_{ki} \right) \setminus C_i \\ &= \bigcup_{k=1}^q (X_{ki} \setminus C_i) \\ &= \bigcup_{k=1}^q R_{ki} \end{aligned}$$

Example:

$$\begin{aligned} V \setminus C_1 &= R_{21} \cup R_{41} \cup R_{31} \\ \{A, D, F, H\} &= \{A\} \cup \{D\} \cup \{F, H\} \end{aligned}$$

# Propagation



**Task:** Calculate  $P(c_i)$ :

In general:

$$P(c_i) = \sum_{v \setminus c_i} \prod_{j=1}^m \psi_j(c_j)$$

Marginalization      Decomposition

$$= \psi_i(c_i) \sum_{v \setminus c_i} \prod_{i \neq j} \psi_j(c_j)$$

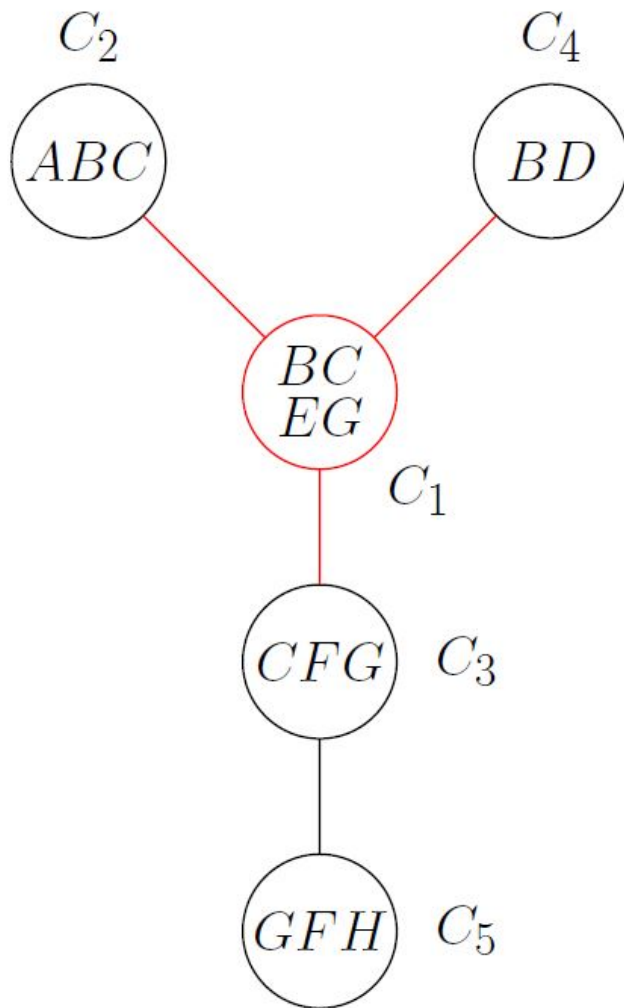
$$= \psi_i(c_i) \sum_{r_{1i} \cup \dots \cup r_{qi}} \prod_{i \neq j} \psi_j(c_j)$$

$$= \psi_i(c_i) \underbrace{\left( \sum_{r_{1i}} \prod_{c_k \in \mathcal{C}_{1i}} \psi_k(c_k) \right)}_{M_{1i}(s_{ij})} \cdots \underbrace{\left( \sum_{r_{qi}} \prod_{c_k \in \mathcal{C}_{qi}} \psi_k(c_k) \right)}_{M_{qi}(s_{ij})}$$

$$= \psi_i(c_i) \prod_{j=1}^q M_{ji}(s_{ij})$$



# Propagation



Example:  $P(c_1)$ :

$$P(c_1) = \psi_1(c_1)M_{21}(s_{12})M_{41}(s_{14})M_{31}(s_{13})$$

$M_{ij}(s_{ij})$  can be simplified further (without proof):

$$\begin{aligned} M_{ij}(s_{ij}) &= \sum_{r_{ij}} \prod_{c_k \in \mathcal{C}_{ij}} \psi_k(c_k) \\ &= \sum_{c_i \setminus s_{ij}} \psi_i(c_i) \prod_{k \neq j} M_{ki}(s_{ki}) \end{aligned}$$

# Final Algorithm

**Input:** Join tree  $(\mathcal{C}, \Psi)$  over set of variables  $V$  and evidence  $E = e$ .

**Output:** The a-posteriori probability  $P(x_i | e)$  for every non-evidential  $X_i$ .

**Initialization:** Incorporate evidence  $E = e$  into potential functions.

**Iterations:**

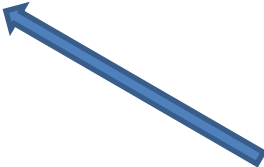
1. For every clique  $C_i$  do: For every neighbor  $B_j$  of  $C_i$  do: If  $C_i$  has received all messages from the *other* neighbors, calculate and send  $M_{ij}(s_{ij})$  to  $B_j$ .
2. Repeat step 1 until no message is calculated.
3. Calculate the joint probability distribution for every clique:

$$P(c_i) \propto \psi_i(c_i) \prod_{j=1}^q M_{ji}(s_{ij})$$

4. For every  $X \in V$  calculate the a-posteriori probability:

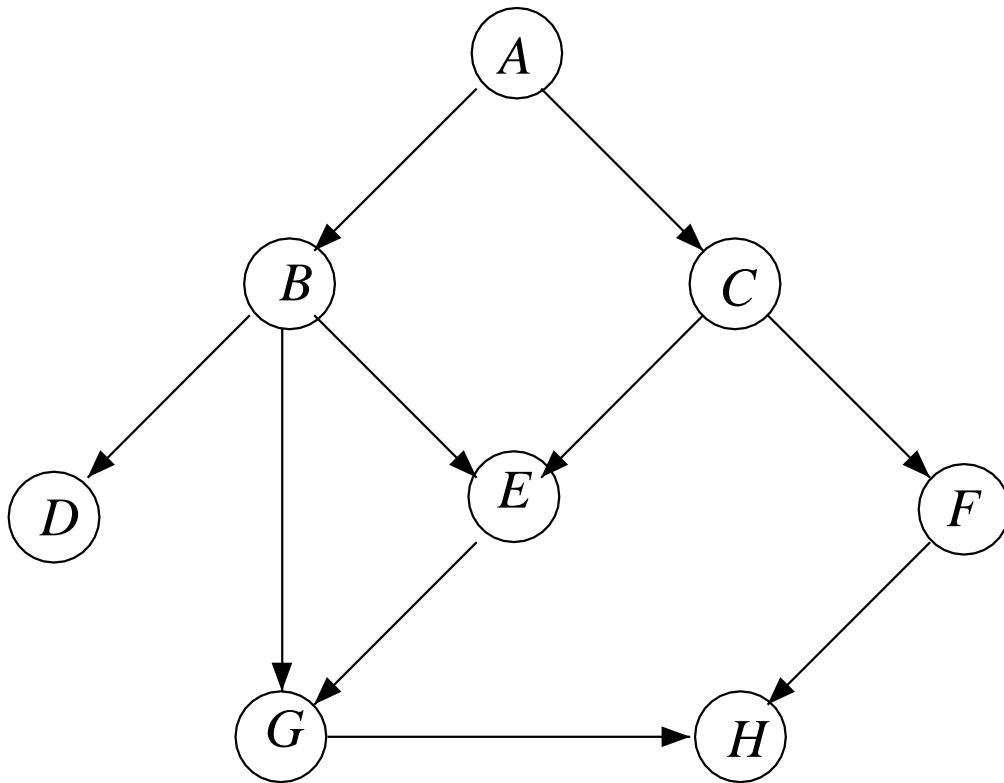
$$P(x_i | e) = \sum_{c_k \setminus x_i} P(c_k)$$

where  $C_k$  is the smallest clique containing  $X_i$ .



The  $\propto$  - sign indicates that the values  $P(c_i)$  need to be normalized if their sum is not 1

# Example 1: Clique Tree Propagation



Goals: Find the marginal distributions and update them when evidence  $H = h_1$  becomes known.

Steps:

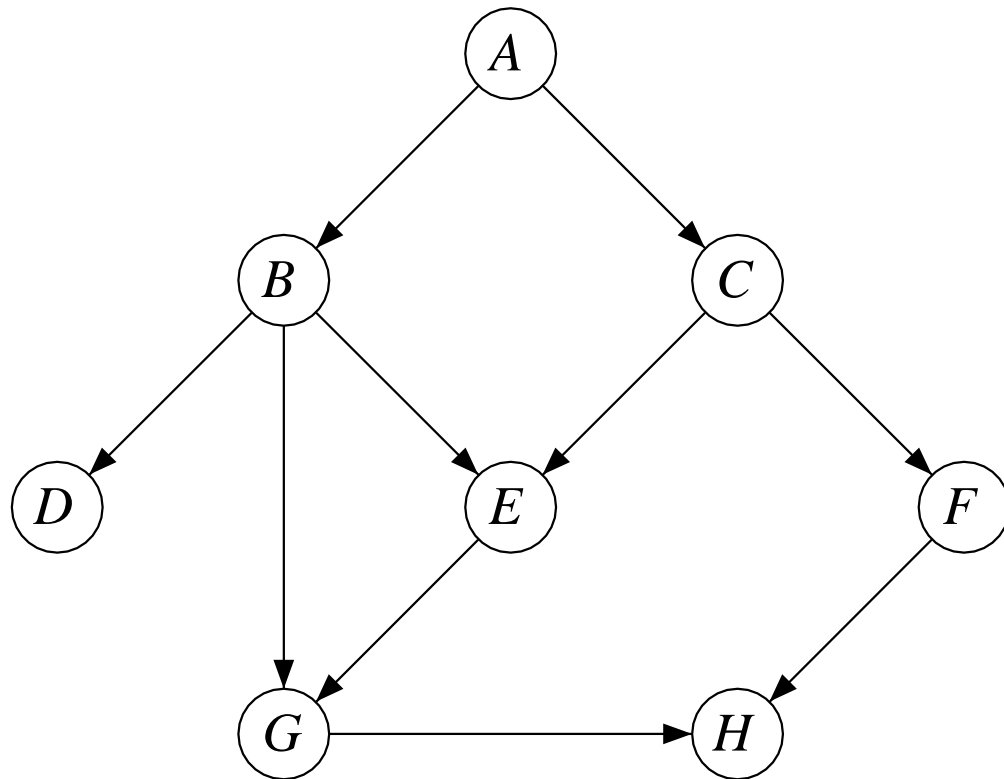
1. Transform network into join-tree.
2. Specify factor potentials.
3. Propagate “zero” evidence to obtain the marginals before evidence is present.
4. Update factor potentials w. r. t. the evidence and do another propagation run.

$P(A)$		$P(B A)$	$a_1$	$a_2$	$P(C A)$	$a_1$	$a_2$	$P(D B)$	$b_1$	$b_2$	$P(F C)$	$c_1$	$c_2$
$a_1$	0.6	$b_1$	0.2	0.1	$c_1$	0.3	0.7	$d_1$	0.4	0.7	$f_1$	0.1	0.4
$a_2$	0.4	$b_2$	0.8	0.9	$c_2$	0.7	0.3	$d_2$	0.6	0.3	$f_2$	0.9	0.6

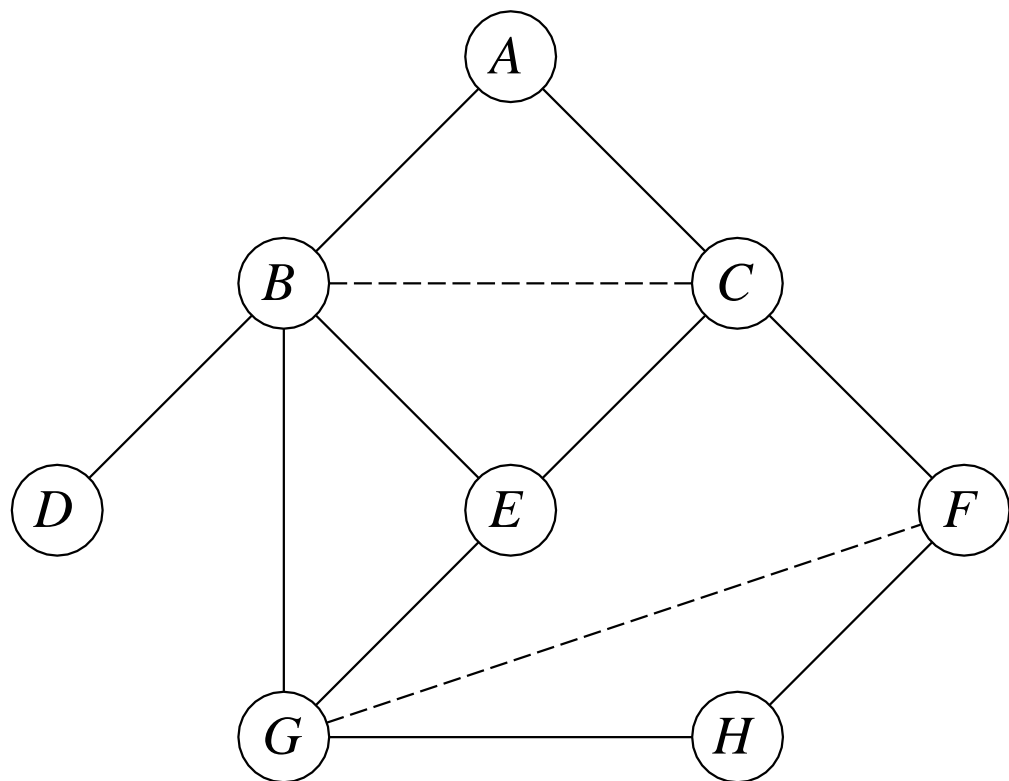
$P(E B,C)$	$b_1$	$b_2$	$P(G B,E)$	$b_1$	$b_2$	$P(H G,F)$	$g_1$	$g_2$
	$c_1$	$c_2$		$e_1$	$e_2$		$f_1$	$f_2$
$e_1$	0.2	0.4	$g_1$	0.95	0.4	$h_1$	0.2	0.4
$e_2$	0.8	0.6	$g_2$	0.05	0.6	$h_2$	0.8	0.6

# Example 1: Find a Join-Tree



**Join-Tree creation**

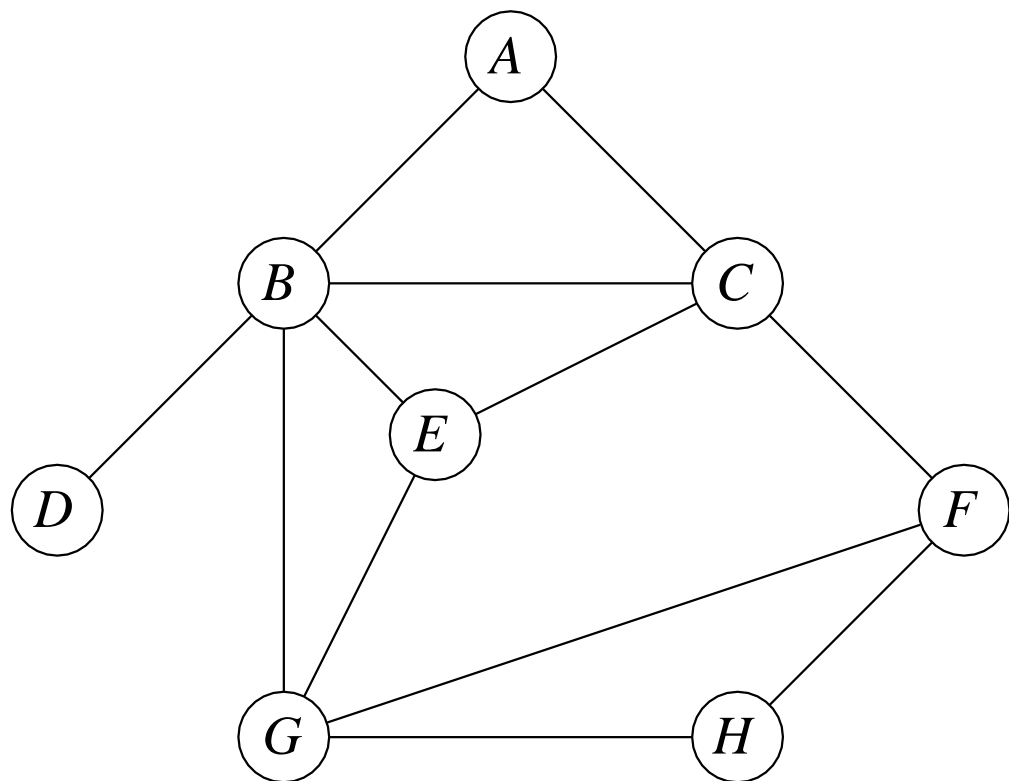
# Example 1: Find a Join-Tree



Join-Tree creation

1. Moralize the graph.

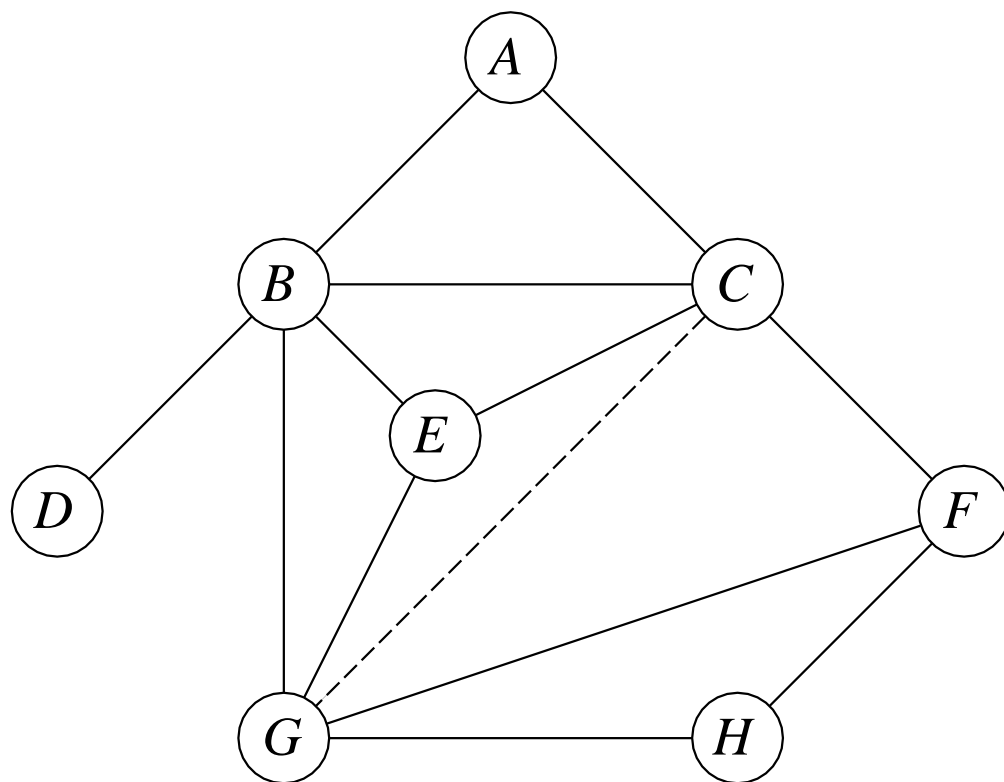
# Example 1: Find a Join-Tree



Join-Tree creation:

1. Moralize the graph.
2. Not yet triangulated.

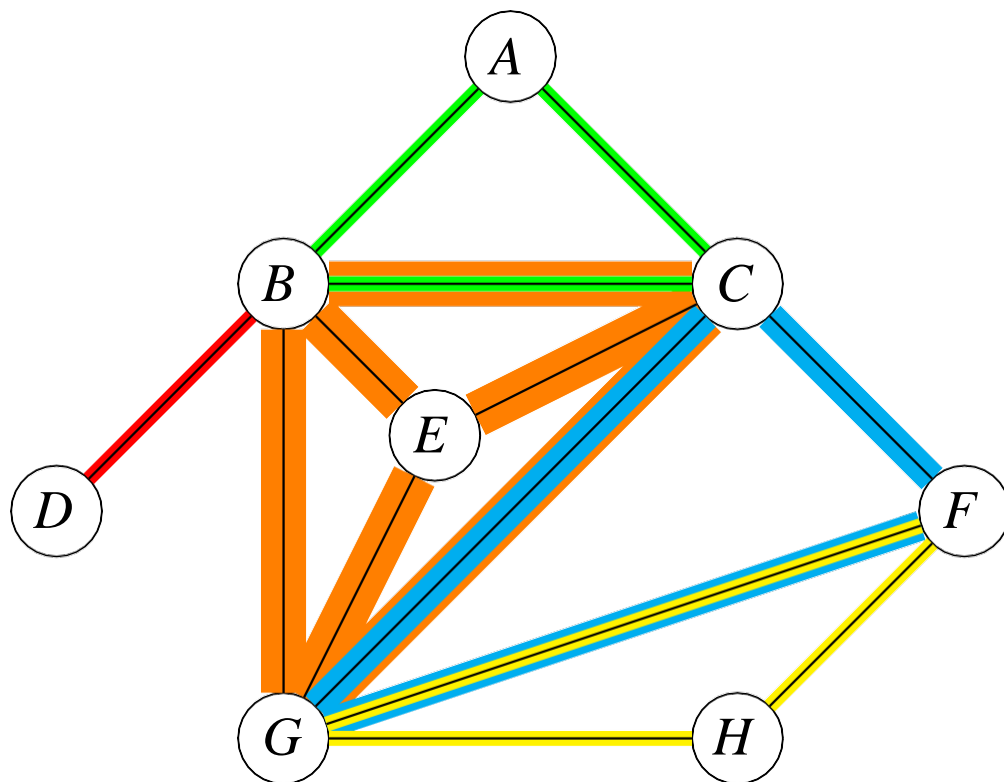
# Example1 : Find a Join-Tree



Join-Tree creation:

1. Moralize the graph.
2. **Triangulate the graph.**

# Example 1: Find a Join-Tree

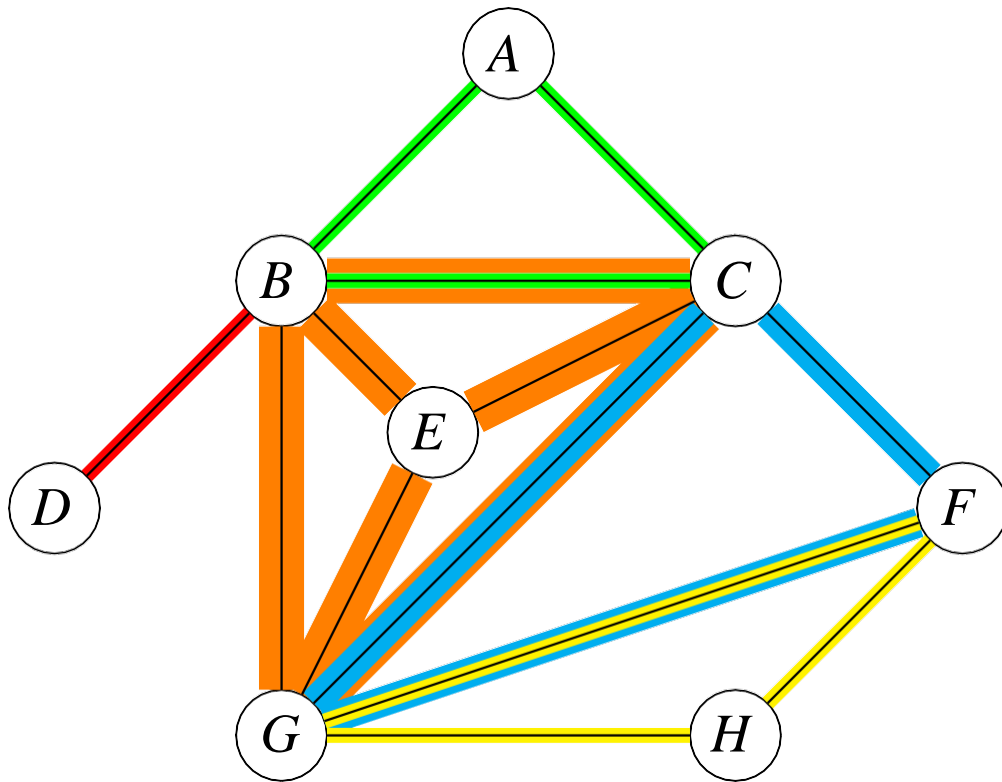


Join-Tree creation:

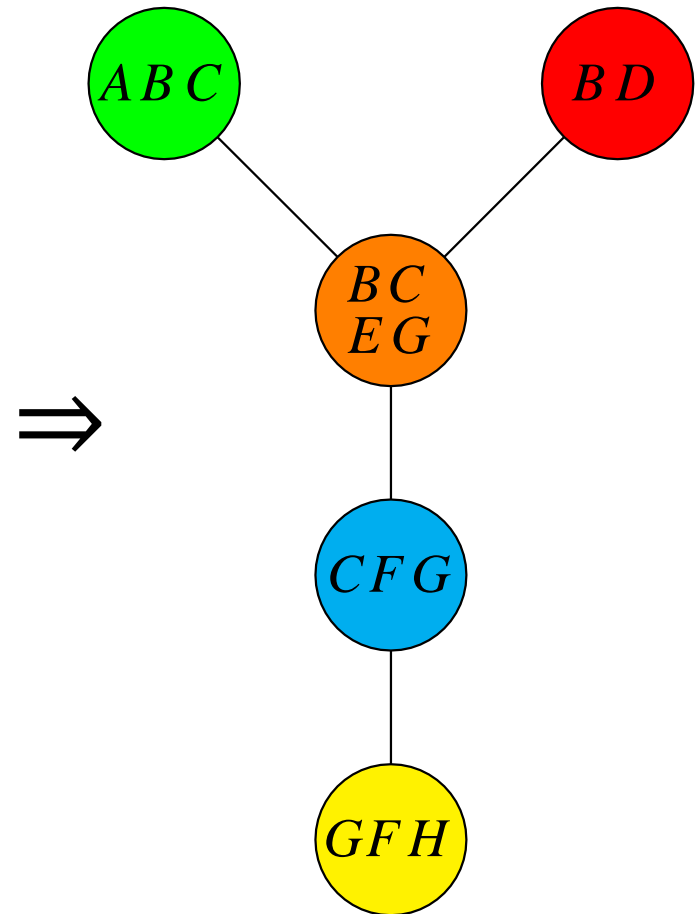
1. Moralize the graph.
2. Triangulate the graph.
3. Identify the maximal cliques.



# Example 1: Find a Join-Tree

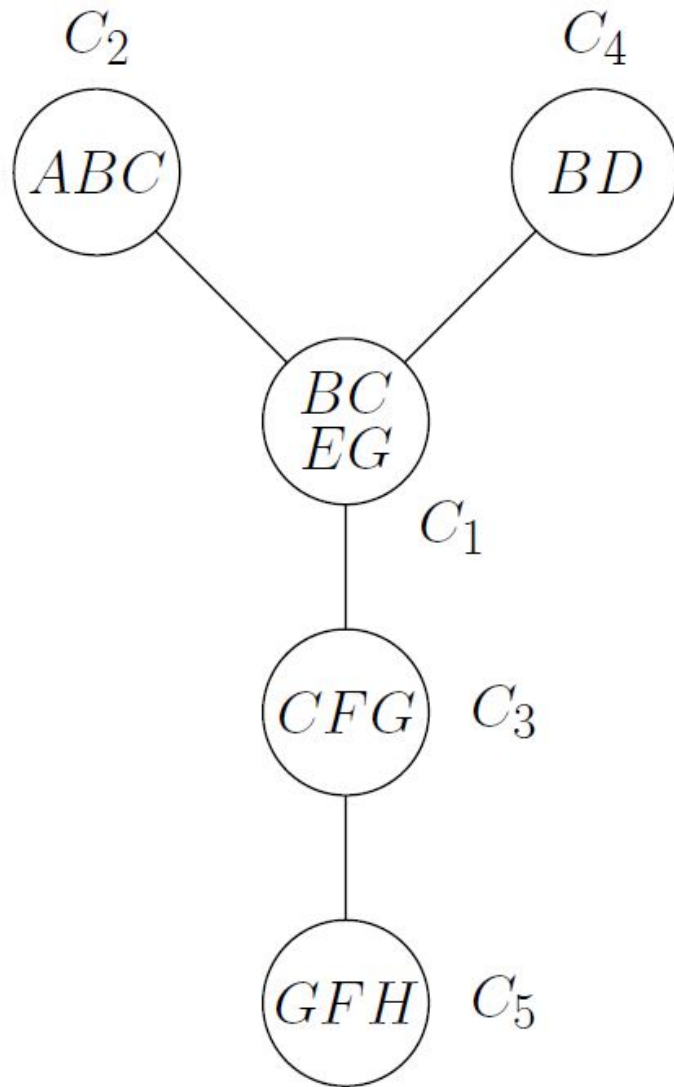


Cliques



One of the possible  
join trees

# Example 1: Specify the Factor Potentials



Decomposition of  $P(A, B, C, D, E, F, G, H)$ :

$$\begin{aligned} P(a, b, c, d, e, f, g, h) &= \prod_{i=1}^5 \Psi_i(c_i) \\ &= \Psi_1(b, c, e, g) \cdot \Psi_2(a, b, c) \\ &\quad \cdot \Psi_3(c, f, g) \cdot \Psi_4(b, d) \\ &\quad \cdot \Psi_5(g, f, h) \end{aligned}$$

**Where to get the factor potentials from?**

# Example 1: Specify the Factor Potentials

As long as the factor potentials multiply together as on the previous slide, we are free to choose them.

**Option 1:** A factor potential of clique  $C_i$  is the product of all conditional probabilities of all node families properly contained in  $C_i$ :

$$\Psi_i(c_i) = 1 \cdot \prod_{\substack{\{X_i\} \cup Y_i \subseteq C_i \wedge \\ \text{parents}(X_i) = Y_i}} P(x_i | y_i)$$

The 1 stresses that if no node family satisfies the product condition, we assign a constant 1 to the potential.

**Option 2:** Choose potentials from the decomposition formula:

$$P\left(\bigcup_{i=1}^n C_i\right) = \frac{\prod_{i=1}^n P(C_i)}{\prod_{j=1}^m P(S_j)}$$

# Example 1: Specify the Factor Potentials

**Option 1:** Factor potentials according to the conditional distributions of the node families of the underlying Bayesian network:

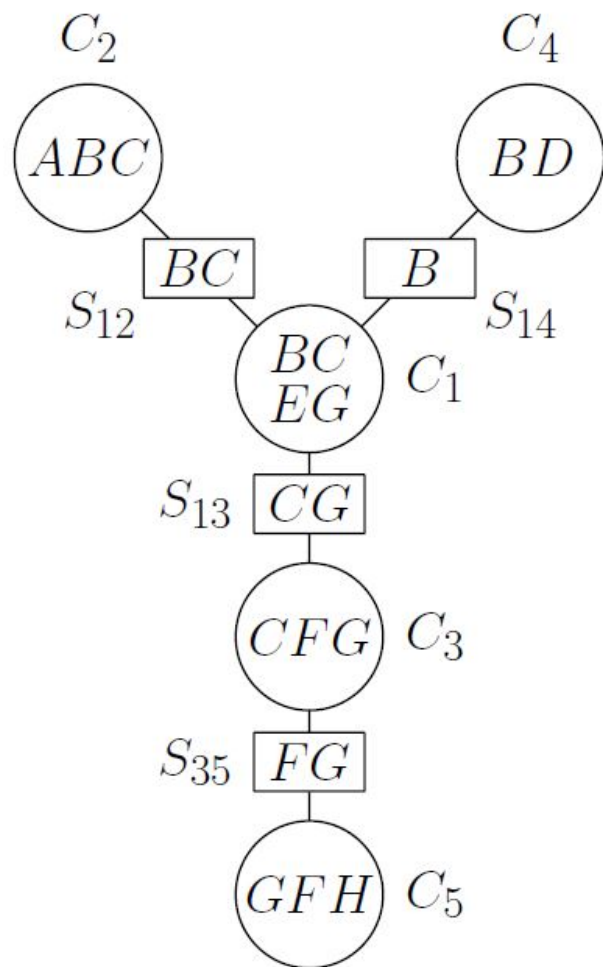
$$\begin{aligned}\Psi_1(b, c, e, g) &= P(e \mid b, c) \cdot P(g \mid e, b) \\ \Psi_2(a, b, c) &= P(b \mid a) \cdot P(c \mid a) \cdot P(a) \\ \Psi_3(c, f, g) &= P(f \mid c) \\ \Psi_4(b, d) &= P(d \mid b) \\ \Psi_5(g, f, h) &= P(h \mid g, f)\end{aligned}$$

(This assignment of factor potentials is used in this example.)

**Option 2:** Factor potentials chosen from the join-tree decomposition:

$$\begin{aligned}\Psi_1(b, c, e, g) &= P(b, e \mid c, g) \\ \Psi_2(a, b, c) &= P(a \mid b, c) \\ \Psi_3(c, f, g) &= P(c \mid f, g) \\ \Psi_4(b, d) &= P(d \mid b) \\ \Psi_5(g, f, h) &= P(h, g, f)\end{aligned}$$

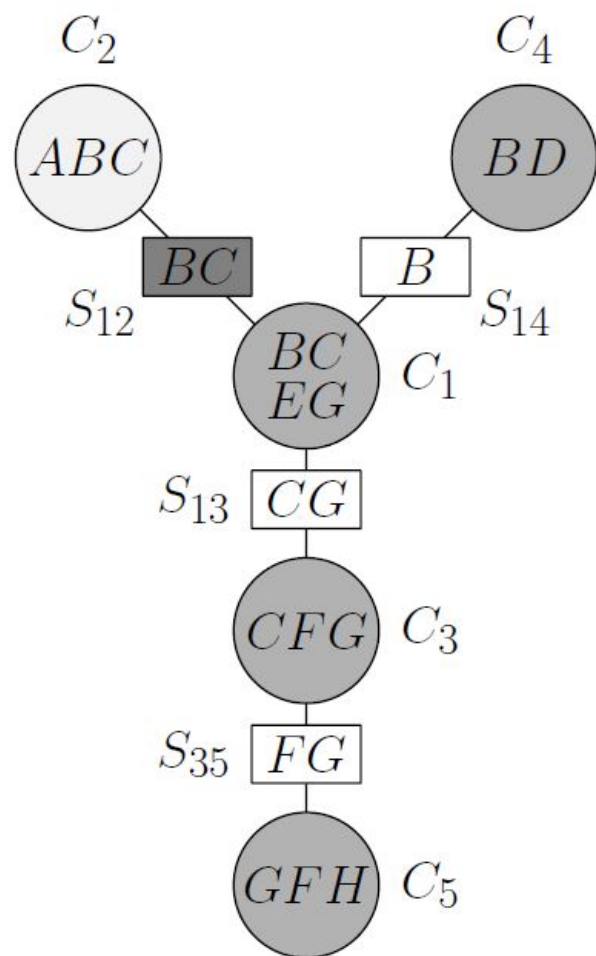
## Example 1: Closer Look on Option 2 (Separation)



Encoded independence statements:

Given any separator, the variables in the cliques on one side become independent of the variables in the cliques on the other side.

## Example 1: Closer Look on Option 2 (Separation)

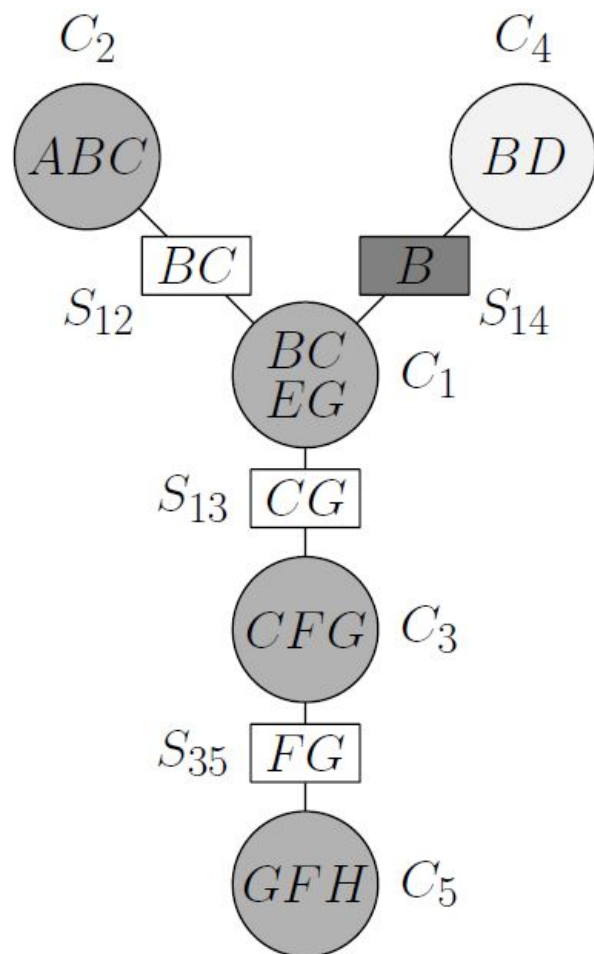


Encoded independence statements:

Given any separator, the variables in the cliques on one side become independent of the variables in the cliques on the other side.

$$A \perp\!\!\!\perp D, E, F, G, H \mid B, C$$

## Example 1: Closer Look on Option 2 (Separation)



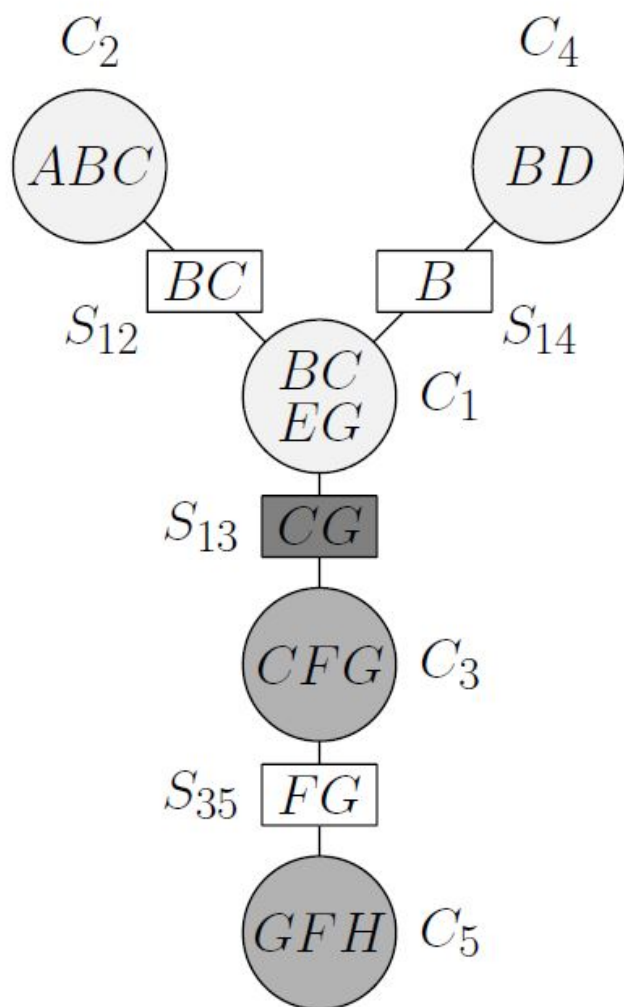
Encoded independence statements:

Given any separator, the variables in the cliques on one side become independent of the variables in the cliques on the other side.

$$A \perp\!\!\!\perp D, E, F, G, H \mid B, C$$

$$D \perp\!\!\!\perp A, C, E, F, G, H \mid B$$

## Example 1: Closer Look on Option 2 (Separation)



Encoded independence statements:

Given any separator, the variables in the cliques on one side become independent of the variables in the cliques on the other side.

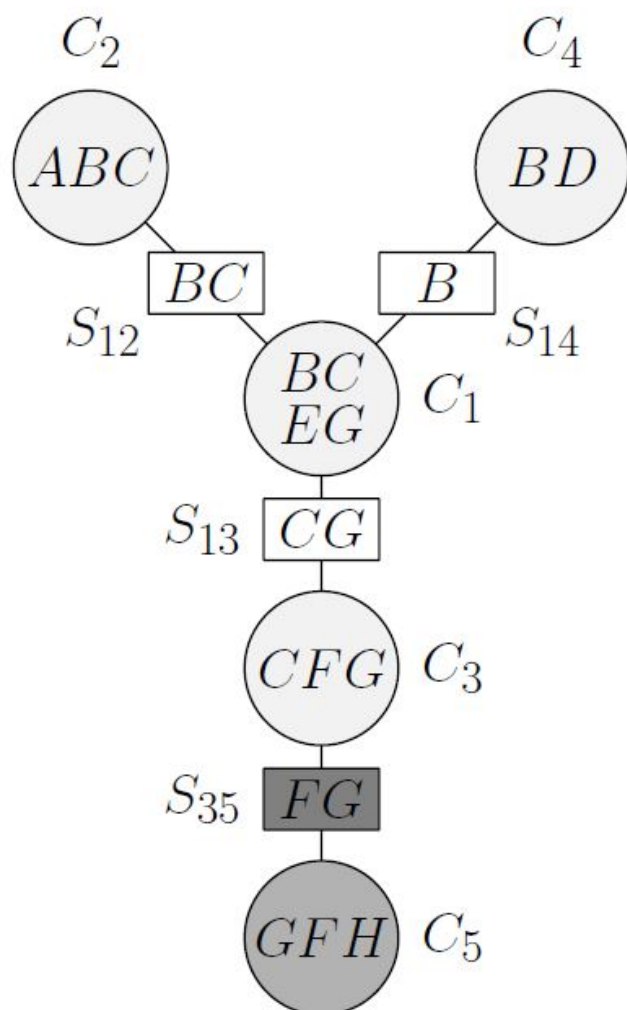
$$A \perp\!\!\!\perp D, E, F, G, H \mid B, C$$

$$D \perp\!\!\!\perp A, C, E, F, G, H \mid B$$

$$A, B, E, D \perp\!\!\!\perp F, H \mid G, C$$



## Example 1: Closer Look on Option 2 (Separation)



Encoded independence statements:

Given any separator, the variables in the cliques on one side become independent of the variables in the cliques on the other side.

$$A \perp\!\!\!\perp D, E, F, G, H \mid B, C$$

$$D \perp\!\!\!\perp A, C, E, F, G, H \mid B$$

$$A, B, E, D \perp\!\!\!\perp F, H \mid G, C$$

$$H \perp\!\!\!\perp A, B, C, D, E \mid F, G$$

## Example 1: Closer Look on Option 2 (Decomposition)

The four separation statements translate into the following independence statements:

$$\begin{aligned} A \perp\!\!\!\perp D, E, F, G, H \mid B, C &\Leftrightarrow P(A \mid B, C, D, E, F, G, H) = P(A \mid B, C) \\ D \perp\!\!\!\perp A, C, E, F, G, H \mid B &\Rightarrow P(D \mid B, C, E, F, G, H) = P(D \mid B) \\ A, B, E, D \perp\!\!\!\perp F, H \mid G, C &\Rightarrow P(B, E \mid G, C, F, H) = P(B, E \mid G, C) \\ H \perp\!\!\!\perp A, B, C, D, E \mid F, G &\Rightarrow P(C \mid F, G, H) = P(C \mid F, G) \end{aligned}$$

According to the chain rule we always have the following relation:

$$\begin{aligned} P(A, B, C, D, E, F, G, H) &= P(A \mid B, C, D, E, F, G, H) \cdot \\ &\quad P(D \mid B, C, E, F, G, H) \cdot \\ &\quad P(B, E \mid C, F, G, H) \cdot \\ &\quad P(C \mid F, G, H) \cdot \\ &\quad P(F, G, H) \end{aligned}$$

## Example 1: Closer Look on Option 2 (decomposition)

The four separation statements translate into the following independence statements:

$$\begin{aligned}A \perp\!\!\!\perp D, E, F, G, H \mid B, C &\Leftrightarrow P(A \mid B, C, D, E, F, G, H) = P(A \mid B, C) \\D \perp\!\!\!\perp A, C, E, F, G, H \mid B &\Rightarrow P(D \mid B, C, E, F, G, H) = P(D \mid B) \\A, B, E, D \perp\!\!\!\perp F, H \mid G, C &\Rightarrow P(B, E \mid G, C, F, H) = P(B, E \mid G, C) \\H \perp\!\!\!\perp A, B, C, D, E \mid F, G &\Rightarrow P(C \mid F, G, H) = P(C \mid F, G)\end{aligned}$$

Exploiting the above independencies yields:

$$\begin{aligned}P(A, B, C, D, E, F, G, H) &= P(A \mid B, C) \cdot \\&\quad P(D \mid B) \cdot \\&\quad P(B, E \mid C, G) \cdot \\&\quad P(C \mid F, G) \cdot \\&\quad P(F, G, H)\end{aligned}$$

## Example 1: Closer Look on Option 2 (Decomposition)

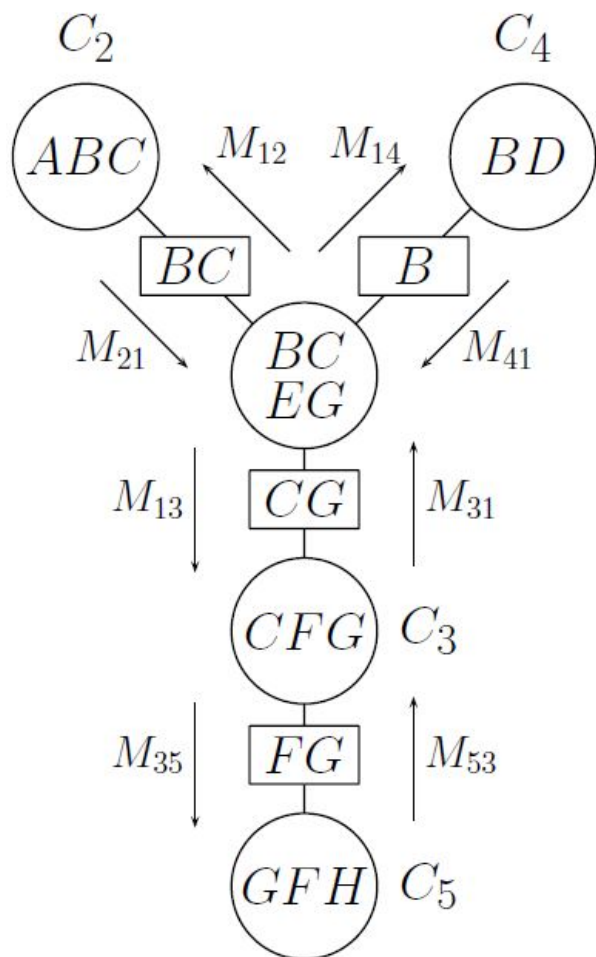
The four separation statements translate into the following independence statements:

$$\begin{aligned}
 A \perp\!\!\!\perp D, E, F, G, H \mid B, C &\Leftrightarrow P(A \mid B, C, D, E, F, G, H) = P(A \mid B, C) \\
 D \perp\!\!\!\perp A, C, E, F, G, H \mid B &\Rightarrow P(D \mid B, C, E, F, G, H) = P(D \mid B) \\
 A, B, E, D \perp\!\!\!\perp F, H \mid G, C &\Rightarrow P(B, E \mid G, C, F, H) = P(B, E \mid G, C) \\
 H \perp\!\!\!\perp A, B, C, D, E \mid F, G &\Rightarrow P(C \mid F, G, H) = P(C \mid F, G)
 \end{aligned}$$

Getting rid of the conditions results in the final decomposition equation:

$$\begin{aligned}
 P(A, B, C, D, E, F, G, H) &= P(A \mid B, C)P(D \mid B)P(B, E \mid C, G)P(C \mid F, G)P(F, G, H) \\
 &= \frac{P(A, B, C)P(D, B)P(B, E, C, G)P(C, F, G)P(F, G, H)}{P(B, C)P(B)P(C, G)P(F, G)} \\
 &= \frac{P(C_1)P(C_2)P(C_3)P(C_4)P(C_5)}{P(S_{12})P(S_{14})P(S_{13})P(S_{35})}
 \end{aligned}$$

# Example 1: Messages to be sent for Propagation



According to the join-tree propagation algorithm, the probability distributions of all clique instantiations  $c_i$  is calculated as follows:

$$P(c_i) \propto \Psi_i(c_i) \prod_{j=1}^q M_{ji}(s_{ij})$$

Spelt out for our example, we get:

$$\begin{aligned} P(c_1) &= P(b, c, e, g) = \Psi_1(b, c, e, g) \cdot M_{21}(b, c) \cdot M_{31}(c, g) \cdot M_{41}(b) \\ P(c_2) &= P(a, b, c) \propto \Psi_2(a, b, c) \cdot M_{12}(b, c) \\ P(c_3) &= P(c, f, g) \propto \Psi_3(c, f, g) \cdot M_{13}(c, g) \cdot M_{53}(f, g) \\ P(c_4) &= P(b, d) \propto \Psi_4(b, d) \cdot M_{14}(b) \\ P(c_5) &= P(f, g, h) \propto \Psi_5(f, g, h) \cdot M_{35}(f, g) \end{aligned}$$

The  $\propto$ -symbol indicates that the right-hand side may not add up to one. In that case we just normalize.

# Example 1: Message Computation Order

The structure of the join-tree imposes a partial ordering according to which the messages need to be computed:

$$M_{41}(b) = \sum_d \Psi_4(b, d)$$

$$M_{53}(f, g) = \sum_h \Psi_5(f, g, h)$$

$$M_{21}(b, c) = \sum_a \Psi_2(a, b, c)$$

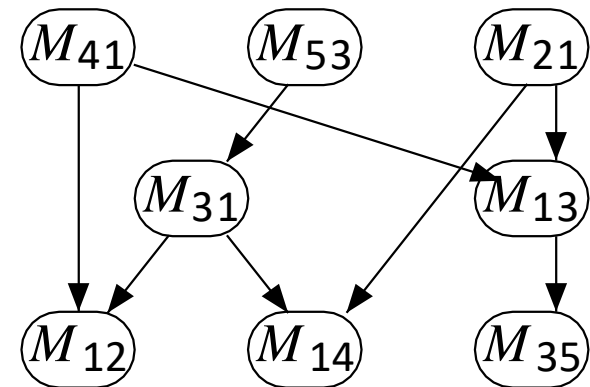
$$M_{31}(c, g) = \sum_f \Psi_3(c, f, g) M_{53}(f, g)$$

$$M_{13}(c, g) = \sum_{b,e} \Psi_1(b, c, e, g) M_{21}(b, c) M_{41}(b)$$

$$M_{12}(b, c) = \sum_{e,g} \Psi_2(b, c, e, g) M_{31}(c, g) M_{41}(b)$$

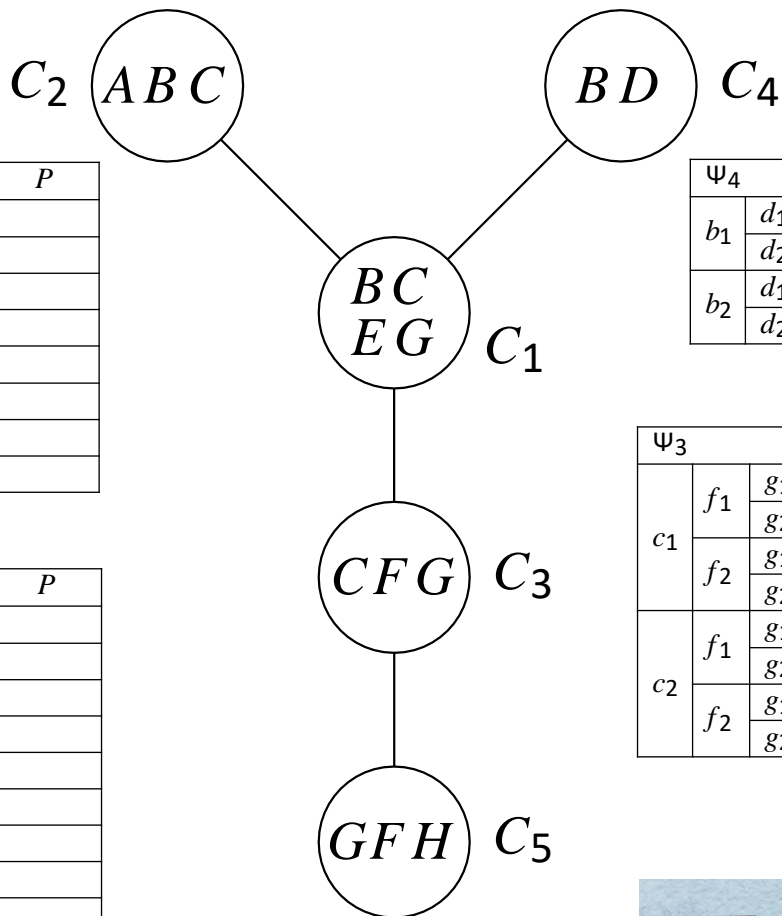
$$M_{14}(b) = \sum_{c,e,g} \Psi_1(b, c, e, g) M_{21}(b, c) M_{31}(c, g)$$

$$M_{35}(f, g) = \sum_c \Psi_3(c, f, g) M_{13}(c, g)$$



Arrows represent is-needed-for relations. Messages on the same level can be computed in any order. Messages are computed level-wise from top to bottom.

# Example 1: Initialization (Potential Layouts)



$\Psi_2$				$P$
$a_1$	$b_1$	$c_1$		
		$c_2$		
	$b_2$	$c_1$		
		$c_2$		
$a_2$	$b_1$	$c_1$		
		$c_2$		
	$b_2$	$c_1$		
		$c_2$		

$\Psi_4$			$P$
$b_1$	$d_1$		
	$d_2$		
$b_2$	$d_1$		
	$d_2$		

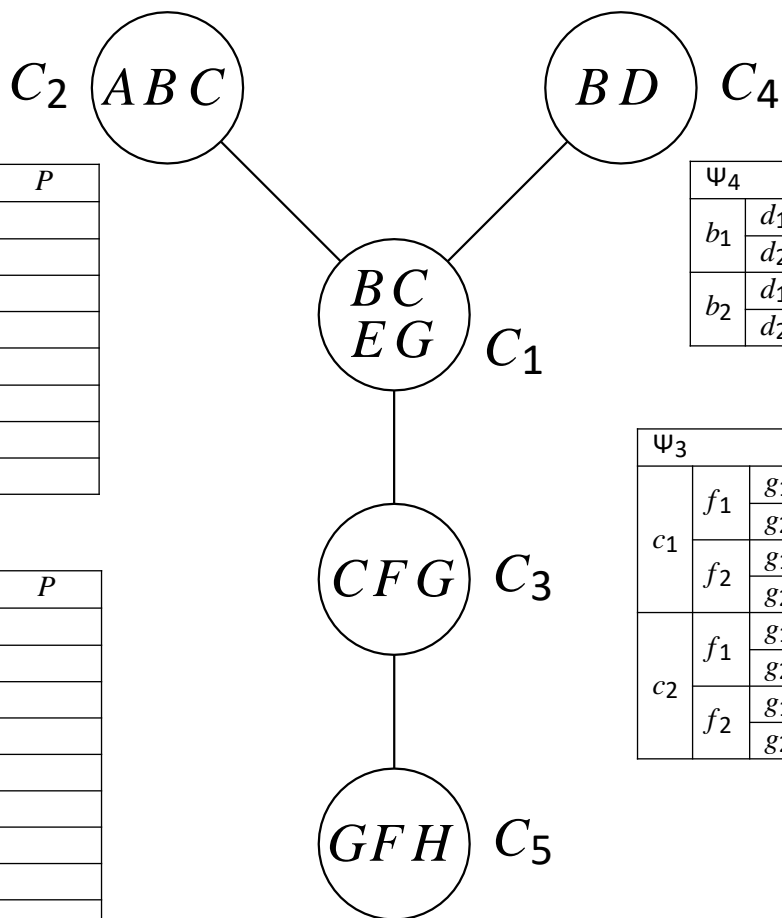
$\Psi_1$					$P$
$b_1$	$c_1$	$e_1$	$g_1$		
			$g_2$		
		$e_2$	$g_1$		
	$g_2$				
	$c_2$	$e_1$	$g_1$		
			$g_2$		
$e_2$		$g_1$			
		$g_2$			
$b_2$	$c_1$	$e_1$	$g_1$		
			$g_2$		
		$e_2$	$g_1$		
	$g_2$				
	$c_2$	$e_1$	$g_1$		
			$g_2$		
$e_2$		$g_1$			
		$g_2$			

$\Psi_3$				$P$
$c_1$	$f_1$	$g_1$		
		$g_2$		
	$f_2$	$g_1$		
		$g_2$		
$c_2$	$f_1$	$g_1$		
		$g_2$		
	$f_2$	$g_1$		
		$g_2$		

$\Psi_5$				$P$
$f_1$	$g_1$	$h_1$		
		$h_2$		
		$h_1$		
	$g_2$	$h_1$		
		$h_2$		
		$h_1$		
$f_2$	$g_1$	$h_1$		
		$h_2$		
		$h_1$		
	$g_2$	$h_1$		
		$h_2$		
		$h_1$		

$P(A)$		$P(B A)$	$a_1$ $a_2$	$P(C A)$	$a_1$ $a_2$	$P(D B)$	$b_1$ $b_2$	$P(F C)$	$c_1$ $c_2$
$a_1$	0.6	$b_1$	0.2 0.1	$c_1$	0.3 0.7	$d_1$	0.4 0.7	$f_1$	0.1 0.4
$a_2$	0.4	$b_2$	0.8 0.9	$c_2$	0.7 0.3	$d_2$	0.6 0.3	$f_2$	0.9 0.6
$P(E B,C)$	$b_1$ $b_2$	$P(G B,E)$	$b_1$ $b_2$	$P(H G,F)$	$g_1$ $g_2$				
	$c_1$ $c_2$ $c_1$ $c_2$		$e_1$ $e_2$ $e_1$ $e_2$		$f_1$ $f_2$ $f_1$ $f_2$				
$e_1$	0.2 0.4 0.3 0.1	$g_1$	0.95 0.4 0.7 0.5	$h_1$	0.2 0.4 0.5 0.7				
$e_2$	0.8 0.6 0.7 0.9	$g_2$	0.05 0.6 0.3 0.5	$h_2$	0.8 0.6 0.5 0.3				

# Example 1: Initialization (Potential Values)



$\Psi_2$				$P$
$a_1$	$b_1$	$c_1$	0.036	
		$c_2$	0.084	
	$b_2$	$c_1$	0.144	
		$c_2$	0.336	
$a_2$	$b_1$	$c_1$	0.028	
		$c_2$	0.012	
	$b_2$	$c_1$	0.252	
		$c_2$	0.108	

$\Psi_4$			$P$
$b_1$	$d_1$	0.4	
	$d_2$	0.6	
$b_2$	$d_1$	0.7	
	$d_2$	0.3	

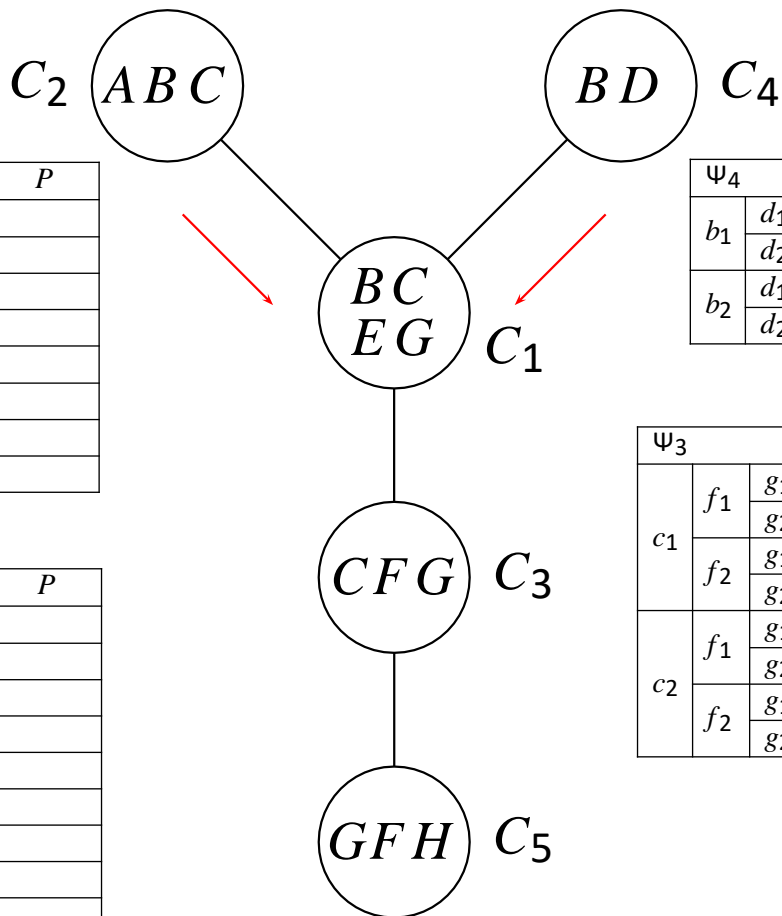
$\Psi_1$				$P$
$b_1$	$c_1$	$e_1$	$g_1$	0.190
		$e_1$	$g_2$	0.010
	$e_2$	$g_1$	0.320	
		$g_2$	0.480	
	$c_2$	$e_1$	$g_1$	0.380
		$e_1$	$g_2$	0.020
$e_2$	$g_1$	0.240		
	$g_2$	0.360		
$b_2$	$c_1$	$e_1$	$g_1$	0.210
		$e_1$	$g_2$	0.090
	$e_2$	$g_1$	0.350	
		$g_2$	0.350	
	$c_2$	$e_1$	$g_1$	0.070
		$e_1$	$g_2$	0.030
$e_2$	$g_1$	0.450		
	$g_2$	0.450		

$\Psi_3$				$P$
$c_1$	$f_1$	$g_1$	0.1	
		$g_2$	0.1	
	$f_2$	$g_1$	0.9	
		$g_2$	0.9	
$c_2$	$f_1$	$g_1$	0.4	
		$g_2$	0.4	
	$f_2$	$g_1$	0.6	
		$g_2$	0.6	

$\Psi_5$				$P$
$f_1$	$g_1$	$h_1$	0.2	
		$h_2$	0.8	
	$g_2$	$h_1$	0.5	
		$h_2$	0.5	
$f_2$	$g_1$	$h_1$	0.4	
		$h_2$	0.6	
	$g_2$	$h_1$	0.7	
		$h_2$	0.3	



# Example 1: Initialization (Sending Messages)



$\Psi_2$				$P$
$a_1$	$b_1$	$c_1$	0.036	
		$c_2$	0.084	
	$b_2$	$c_1$	0.144	
		$c_2$	0.336	
$a_2$	$b_1$	$c_1$	0.028	
		$c_2$	0.012	
	$b_2$	$c_1$	0.252	
		$c_2$	0.108	

$\Psi_4$			$P$
$b_1$	$d_1$	0.4	
	$d_2$	0.6	
$b_2$	$d_1$	0.7	
	$d_2$	0.3	

$$M_{21} = (b_{1,c_1} \ b_{1,c_2} \ b_{2,c_1} \ b_{2,c_2}) = (0.06, 0.10, 0.40, 0.44)$$

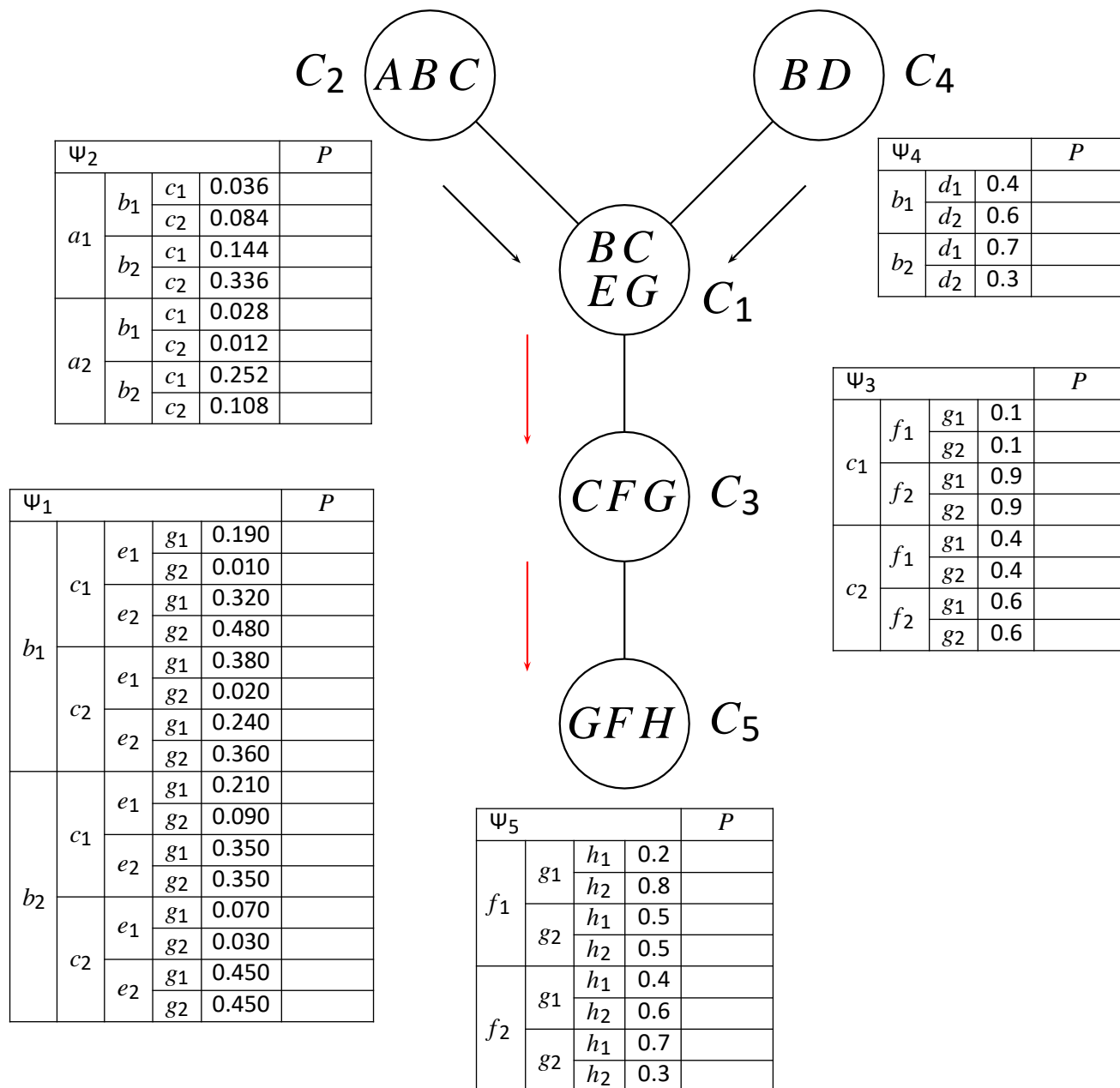
$$M_{41} = (b_1 \ b_2) = (1, 1)$$

$\Psi_1$					$P$
$b_1$	$c_1$	$e_1$	$g_1$	0.190	
			$g_2$	0.010	
	$c_2$	$e_1$	$g_1$	0.320	
			$g_2$	0.480	
	$c_1$	$e_2$	$g_1$	0.380	
			$g_2$	0.020	
$b_2$	$c_1$	$e_1$	$g_1$	0.240	
			$g_2$	0.360	
	$c_2$	$e_1$	$g_1$	0.210	
			$g_2$	0.090	
	$c_1$	$e_2$	$g_1$	0.350	
			$g_2$	0.350	
$c_2$	$e_1$	$g_1$	0.070		
		$g_2$	0.030		
$c_2$	$e_2$	$g_1$	0.450		
		$g_2$	0.450		

$\Psi_3$				$P$
$c_1$	$f_1$	$g_1$	0.1	
		$g_2$	0.1	
	$f_2$	$g_1$	0.9	
		$g_2$	0.9	
$c_2$	$f_1$	$g_1$	0.4	
		$g_2$	0.4	
	$f_2$	$g_1$	0.6	
		$g_2$	0.6	

$\Psi_5$				$P$
$f_1$	$g_1$	$h_1$	0.2	
		$h_2$	0.8	
	$g_2$	$h_1$	0.5	
		$h_2$	0.5	
$f_2$	$g_1$	$h_1$	0.4	
		$h_2$	0.6	
	$g_2$	$h_1$	0.7	
		$h_2$	0.3	

# Example 1: Initialization (Sending Messages)



$$M_{21} = (b_{1,c_1} \ b_{1,c_2} \ b_{2,c_1} \ b_{2,c_2})$$

$$= (0.06, 0.10, 0.40, 0.44)$$

$$M_{41} = (b_1 \ b_2)$$

$$= (1, 1)$$

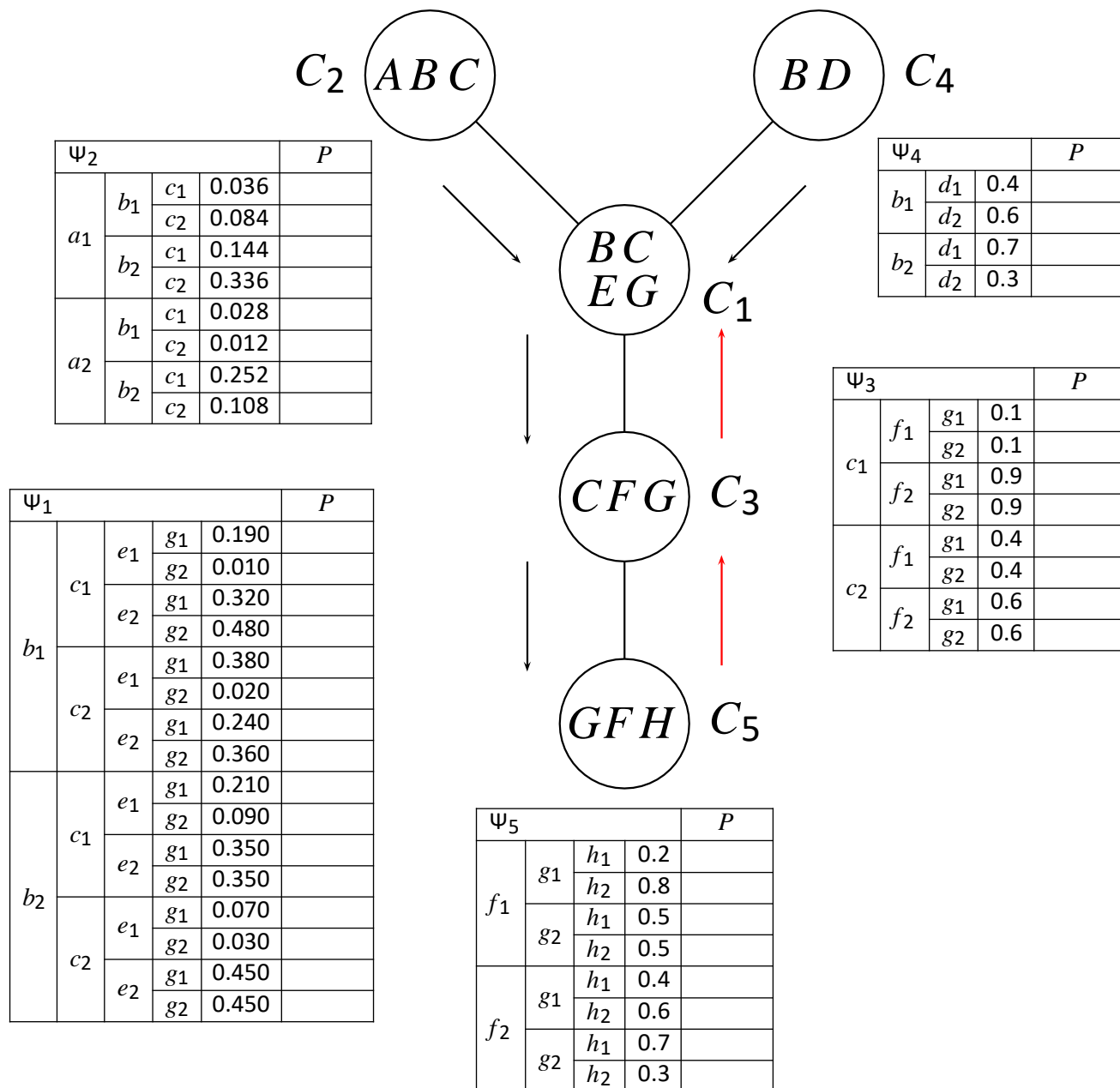
$$M_{13} = (c_{1,g_1} \ c_{1,g_2} \ c_{2,g_1} \ c_{2,g_2})$$

$$= (0.254, 0.206, 0.290, 0.250)$$

$$M_{35} = (f_{1,g_1} \ f_{1,g_2} \ f_{2,g_1} \ f_{2,g_2})$$

$$= (0.14, 0.12, 0.40, 0.33)$$

# Example 1: Initialization (Sending Messages)



$$M_{21} = (b_{1,c_1} \ b_{1,c_2} \ b_{2,c_1} \ b_{2,c_2})$$

$$M_{41} = (b_1 \ b_2)$$

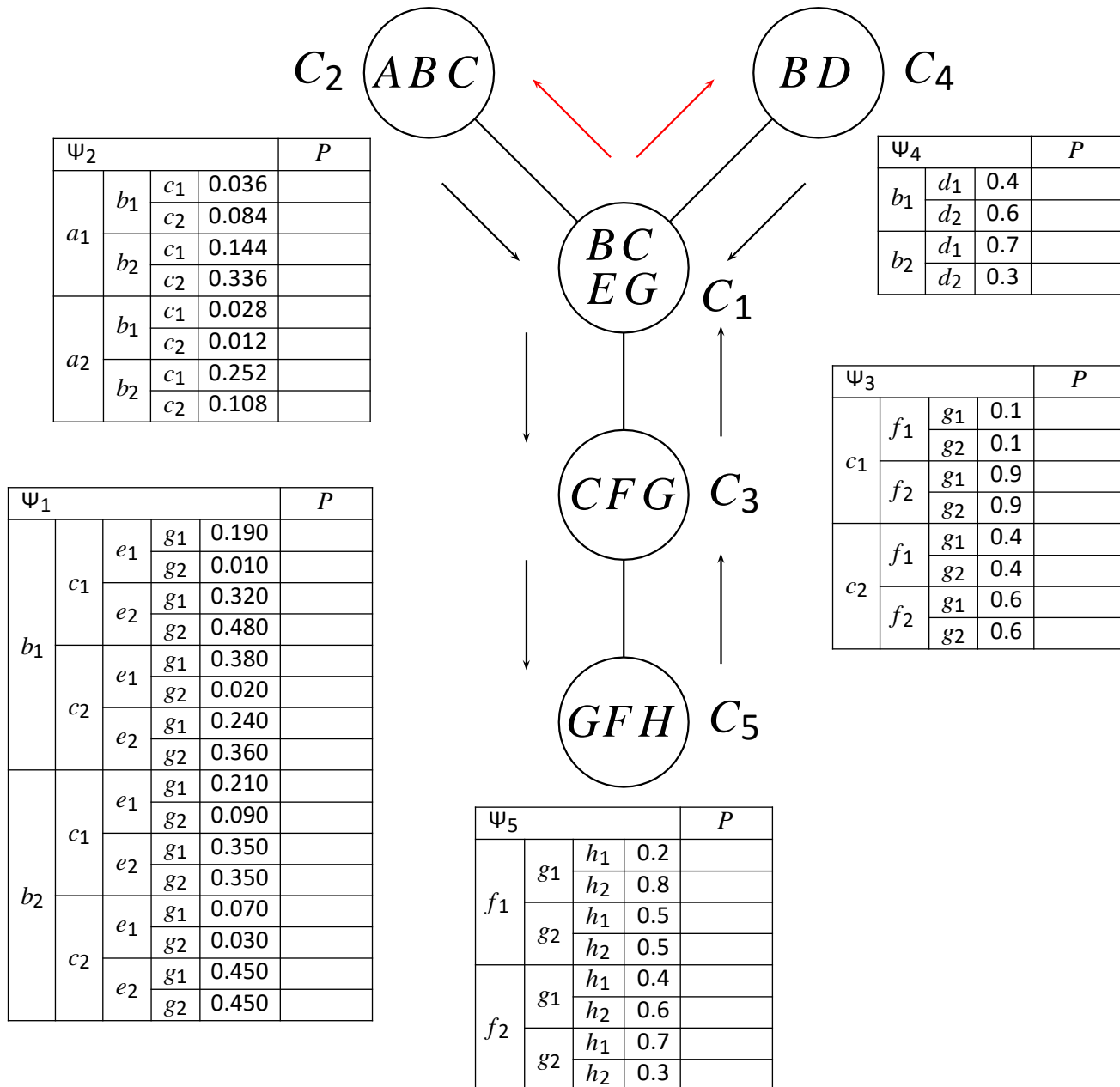
$$M_{13} = (c_{1,g_1} \ c_{1,g_2} \ c_{2,g_1} \ c_{2,g_2})$$

$$M_{35} = (f_{1,g_1} \ f_{1,g_2} \ f_{2,g_1} \ f_{2,g_2})$$

$$M_{53} = (1, 1, 1, 1)$$

$$M_{31} = (c_{1,g_1} \ c_{1,g_2} \ c_{2,g_1} \ c_{2,g_2})$$

# Example 1: Initialization (Sending Messages)



$$M_{21} = (b_{1,c_1} \ b_{1,c_2} \ b_{2,c_1} \ b_{2,c_2})$$

$$= (0.06, 0.10, 0.40, 0.44)$$

$$M_{41} = (b_1 \ b_2)$$

$$= (1, 1)$$

$$M_{13} = (c_{1,g_1} \ c_{1,g_2} \ c_{2,g_1} \ c_{2,g_2})$$

$$= (0.254, 0.206, 0.290, 0.250)$$

$$M_{35} = (f_{1,g_1} \ f_{1,g_2} \ f_{2,g_1} \ f_{2,g_2})$$

$$= (0.14, 0.12, 0.40, 0.33)$$

$$M_{53} = (f_{1,g_1} \ f_{1,g_2} \ f_{2,g_1} \ f_{2,g_2})$$

$$= (1, 1, 1, 1)$$

$$M_{31} = (c_{1,g_1} \ c_{1,g_2} \ c_{2,g_1} \ c_{2,g_2})$$

$$= (1, 1, 1, 1)$$

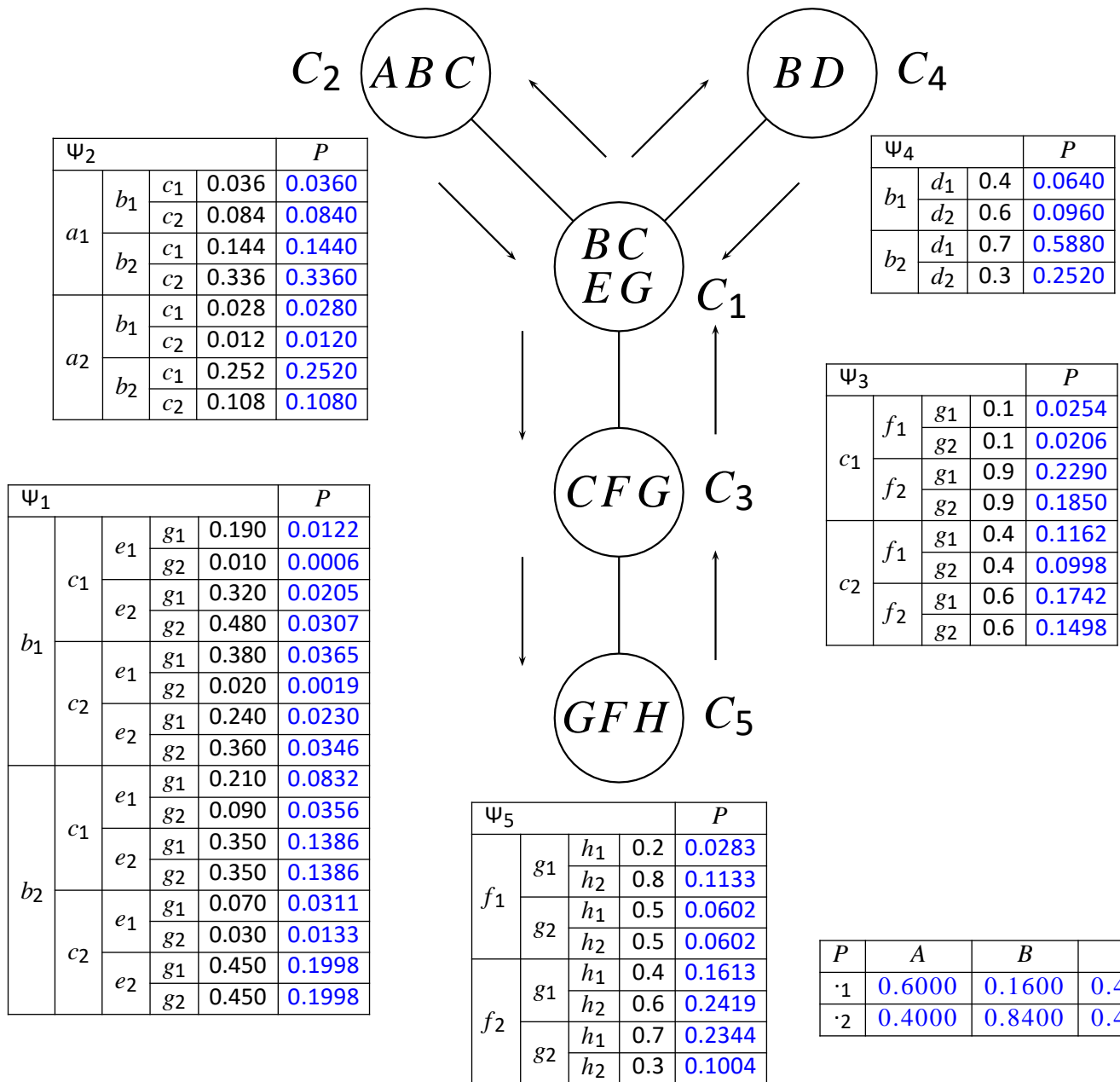
$$M_{12} = (b_{1,c_1} \ b_{1,c_2} \ b_{2,c_1} \ b_{2,c_2})$$

$$= (1, 1, 1, 1)$$

$$M_{14} = (b_1 \ b_2)$$

$$= (0.16, 0.84)$$

# Example 1: Initialization Complete



$$M_{21} = \begin{pmatrix} b_{1,c_1} & b_{1,c_2} & b_{2,c_1} & b_{2,c_2} \\ 0.06, & 0.10, & 0.40, & 0.44 \end{pmatrix}$$

$$M_{41} = \begin{pmatrix} b_1 & b_2 \\ 1, & 1 \end{pmatrix}$$

$$M_{13} = \begin{pmatrix} c_{1,g_1} & c_{1,g_2} & c_{2,g_1} & c_{2,g_2} \\ 0.254, & 0.206, & 0.290, & 0.250 \end{pmatrix}$$

$$M_{35} = \begin{pmatrix} f_{1,g_1} & f_{1,g_2} & f_{2,g_1} & f_{2,g_2} \\ 0.14, & 0.12, & 0.40, & 0.33 \end{pmatrix}$$

$$M_{53} = \begin{pmatrix} f_{1,g_1} & f_{1,g_2} & f_{2,g_1} & f_{2,g_2} \\ 1, & 1, & 1, & 1 \end{pmatrix}$$

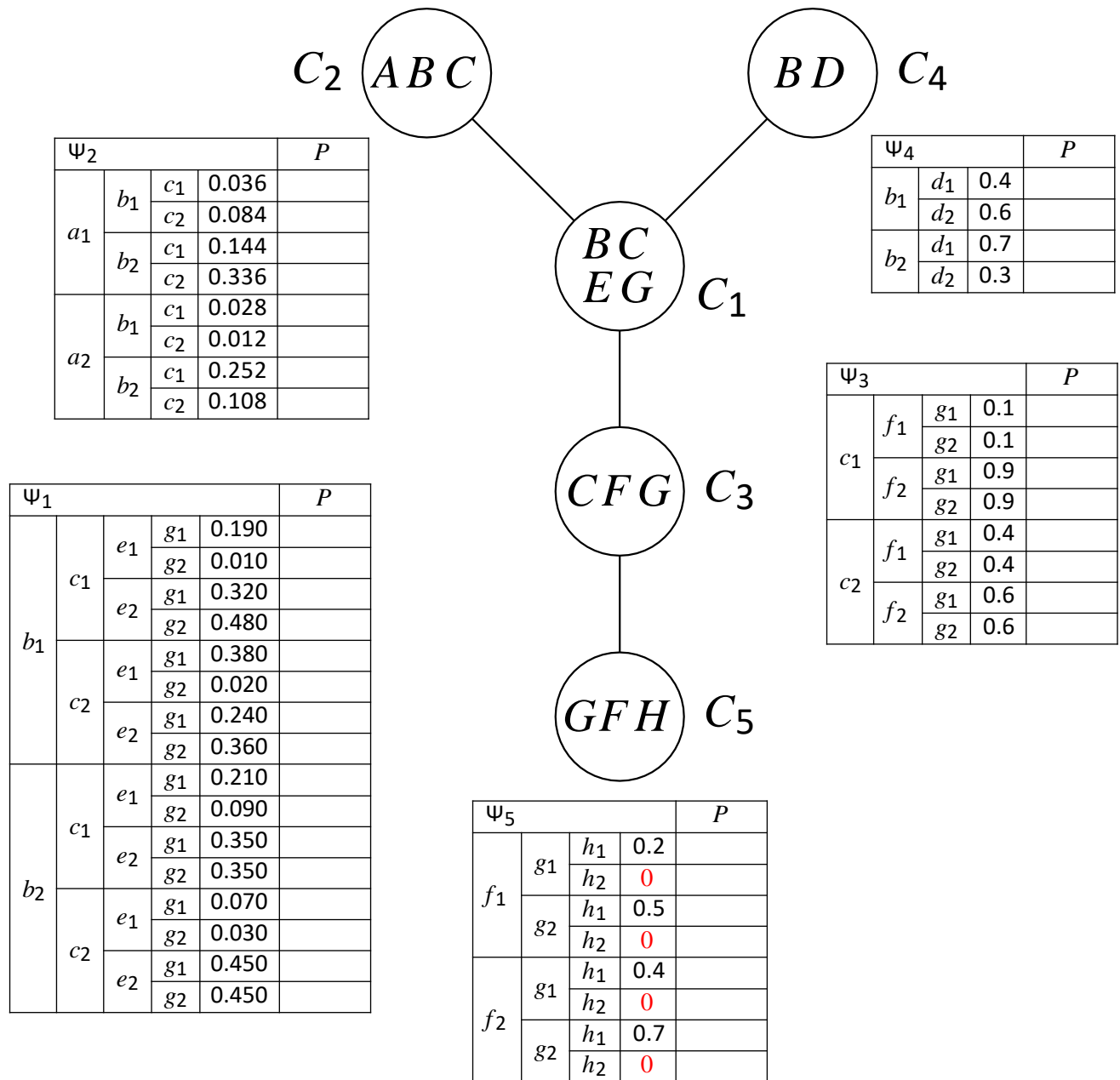
$$M_{31} = \begin{pmatrix} c_{1,g_1} & c_{1,g_2} & c_{2,g_1} & c_{2,g_2} \\ 1, & 1, & 1, & 1 \end{pmatrix}$$

$$M_{12} = \begin{pmatrix} b_{1,c_1} & b_{1,c_2} & b_{2,c_1} & b_{2,c_2} \\ 1, & 1, & 1, & 1 \end{pmatrix}$$

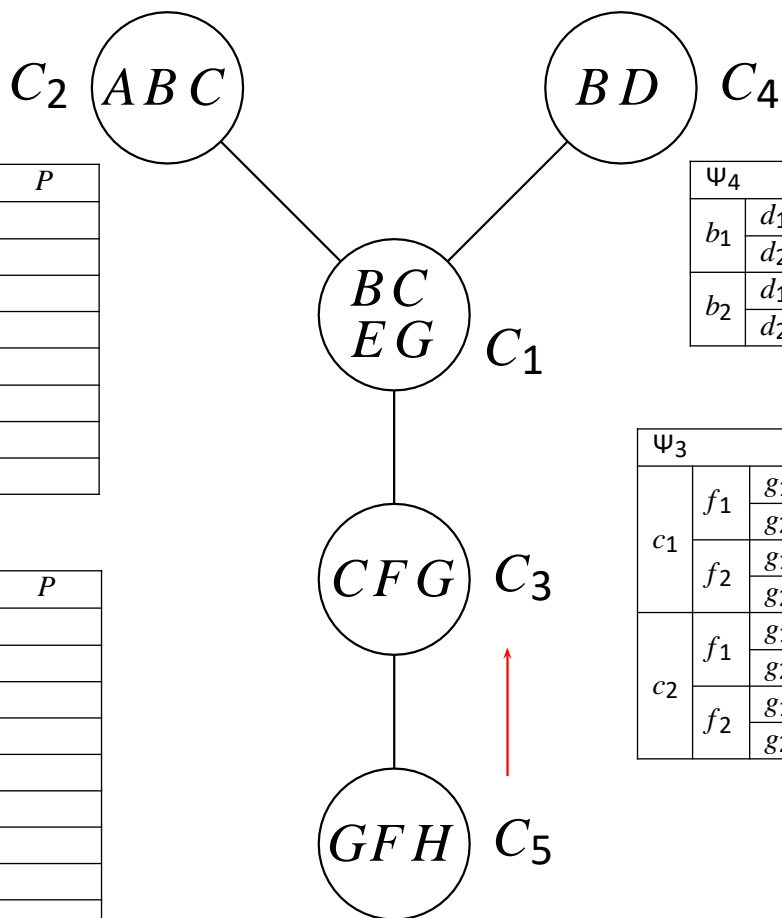
$$M_{14} = \begin{pmatrix} b_1 & b_2 \\ 0.16, & 0.84 \end{pmatrix}$$

$P$	A	B	C	D	E	F	G	H
$\cdot 1$	0.6000	0.1600	0.4600	0.6520	0.2144	0.2620	0.5448	0.4842
$\cdot 2$	0.4000	0.8400	0.4500	0.3480	0.7856	0.7380	0.4552	0.5158

# Example 1: Evidence $H = h_1$ (Altering Potentials)



# Example 1: Evidence $H = h_1$ (Sending Messages)



$\Psi_2$				$P$
$a_1$	$b_1$	$c_1$	0.036	
		$c_2$	0.084	
	$b_2$	$c_1$	0.144	
		$c_2$	0.336	
$a_2$	$b_1$	$c_1$	0.028	
		$c_2$	0.012	
	$b_2$	$c_1$	0.252	
		$c_2$	0.108	

$\Psi_4$			$P$
$b_1$	$d_1$	0.4	
	$d_2$	0.6	
$b_2$	$d_1$	0.7	
	$d_2$	0.3	

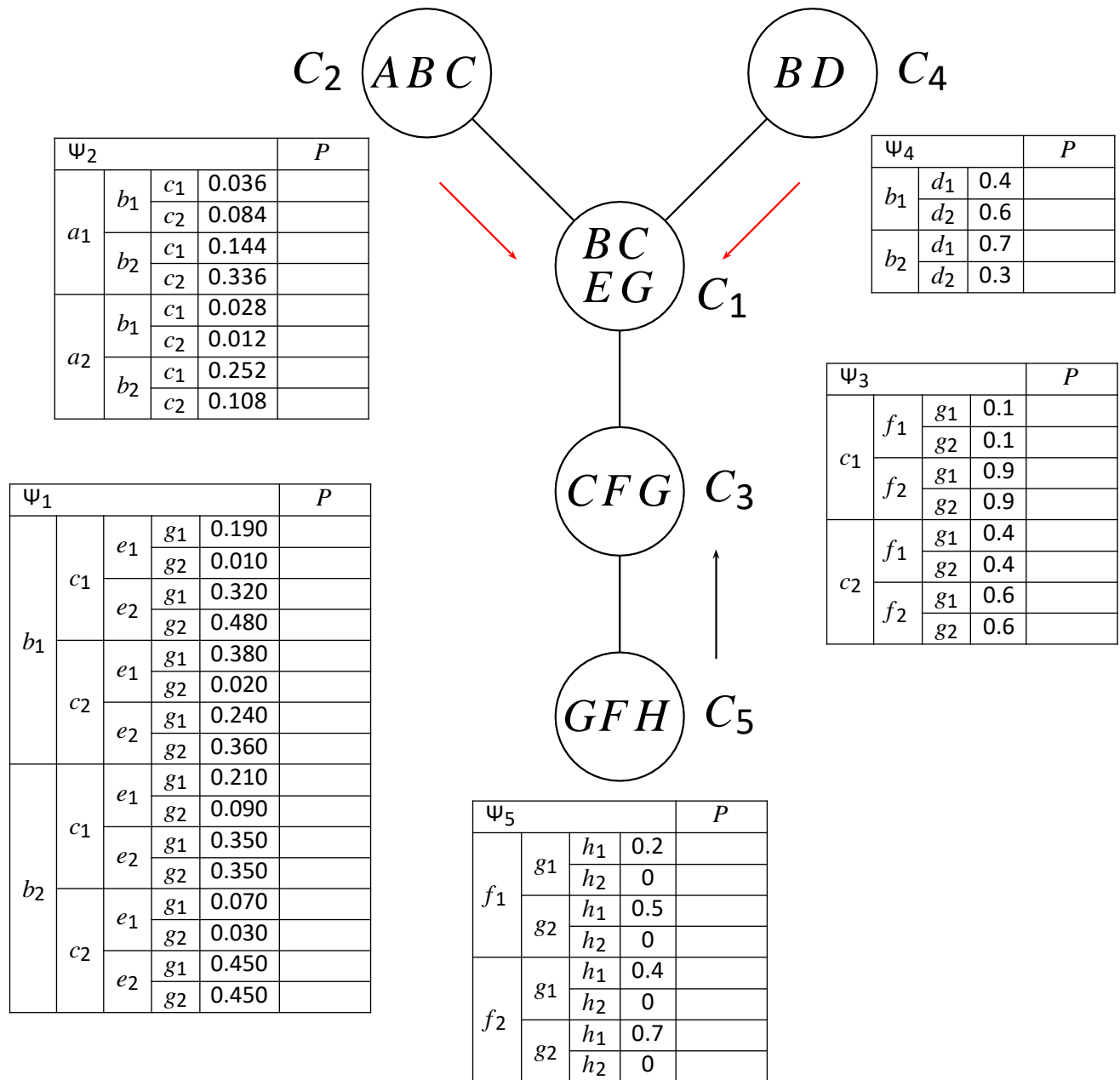
$$M_{53} = \begin{pmatrix} f_{1,g1} & f_{1,g2} & f_{2,g1} & f_{2,g2} \\ 0.2 & 0.5 & 0.4 & 0.7 \end{pmatrix}$$

$\Psi_1$				$P$
$b_1$	$c_1$	$e_1$	$g_1$	0.190
		$e_1$	$g_2$	0.010
	$c_2$	$e_1$	$g_1$	0.320
		$e_2$	$g_2$	0.480
	$c_1$	$e_1$	$g_1$	0.380
		$e_2$	$g_2$	0.020
$b_2$	$c_1$	$e_1$	$g_1$	0.240
		$e_2$	$g_2$	0.360
	$c_2$	$e_1$	$g_1$	0.210
		$e_2$	$g_2$	0.090
	$c_1$	$e_1$	$g_1$	0.350
		$e_2$	$g_2$	0.350
$c_2$	$e_1$	$g_1$	0.070	
	$e_2$	$g_2$	0.450	

$\Psi_3$				$P$
$c_1$	$f_1$	$g_1$	0.1	
		$g_2$	0.1	
	$f_2$	$g_1$	0.9	
		$g_2$	0.9	
$c_2$	$f_1$	$g_1$	0.4	
		$g_2$	0.4	
	$f_2$	$g_1$	0.6	
		$g_2$	0.6	

$\Psi_5$				$P$
$f_1$	$g_1$	$h_1$	0.2	
		$h_2$	0	
	$g_2$	$h_1$	0.5	
		$h_2$	0	
$f_2$	$g_1$	$h_1$	0.4	
		$h_2$	0	
	$g_2$	$h_1$	0.7	
		$h_2$	0	

# Example 1: Step 4: Evidence $H = h_1$ (Sending Messages)



$$M_{53} = (f_{1,g1} \ f_{1,g2} \ f_{2,g1} \ f_{2,g2})$$

$$= (0.2, 0.5, 0.4, 0.7)$$

$$M_{21} = (b_{1,c1} \ b_{1,c2} \ b_{2,c1} \ b_{2,c2})$$

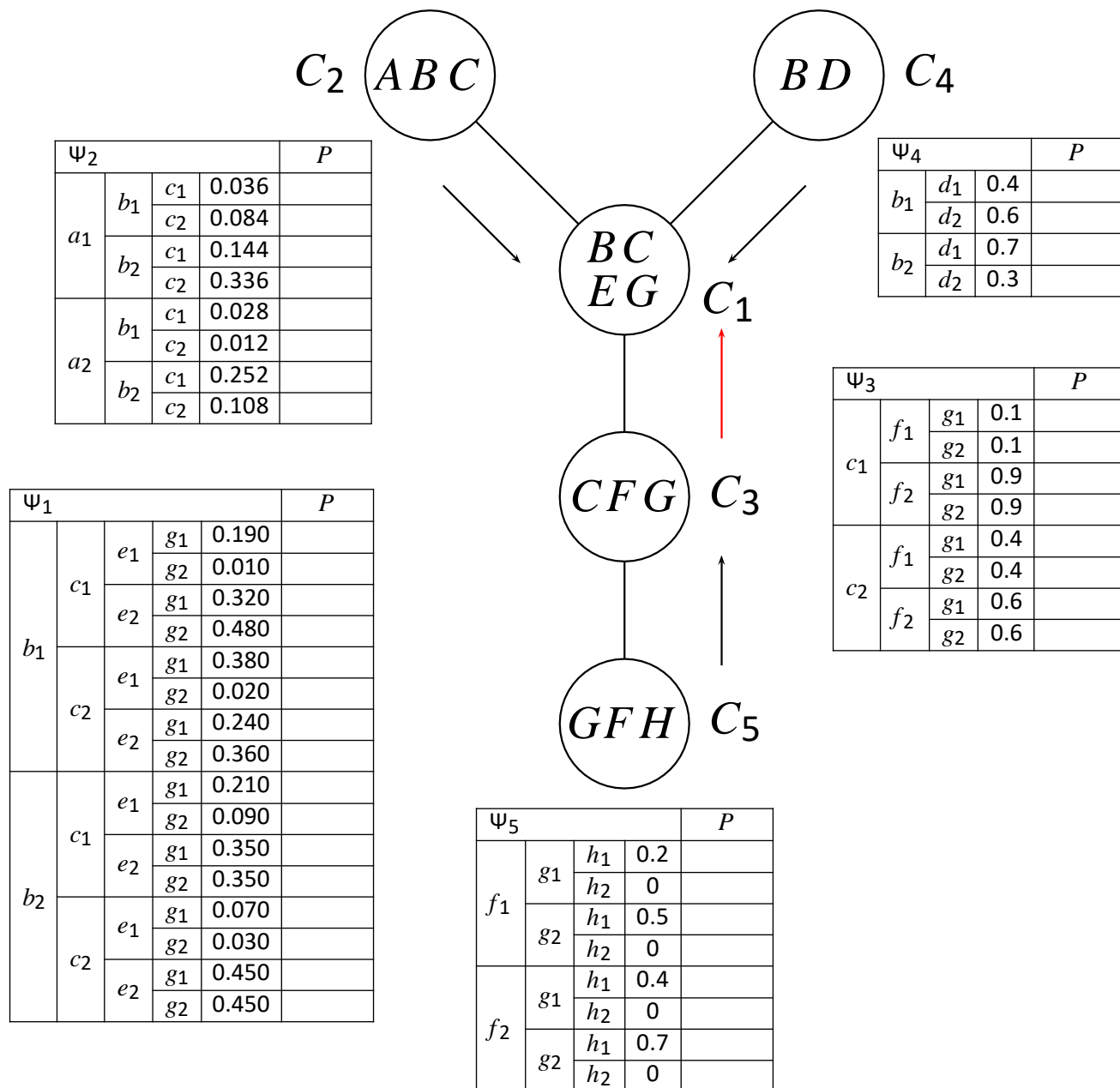
$$= (0.06, 0.10, 0.40, 0.44)$$

$$M_{41} = (b_1 \ b_2)$$

$$= (1, 1)$$



# Example 1: Evidence $H = h_1$ (Sending Messages)



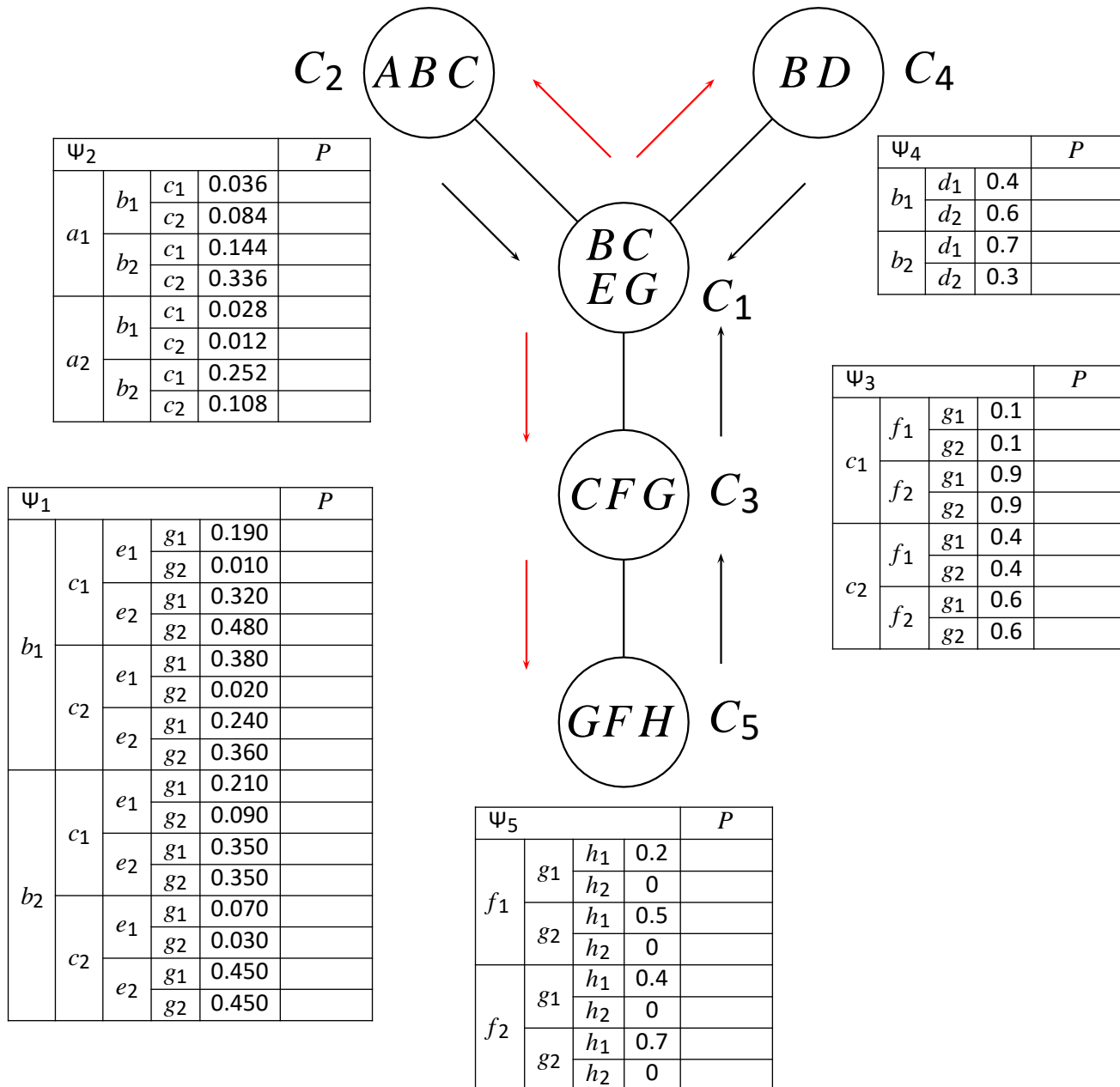
$$M_{53} = \begin{pmatrix} f_{1,g_1} & f_{1,g_2} & f_{2,g_1} & f_{2,g_2} \\ 0.2 & 0.5 & 0.4 & 0.7 \end{pmatrix}$$

$$M_{21} = \begin{pmatrix} b_{1,c_1} & b_{1,c_2} & b_{2,c_1} & b_{2,c_2} \\ 0.06 & 0.10 & 0.40 & 0.44 \end{pmatrix}$$

$$M_{41} = \begin{pmatrix} b_1 & b_2 \\ 1 & 1 \end{pmatrix}$$

$$M_{31} = \begin{pmatrix} c_{1,g_1} & c_{1,g_2} & c_{2,g_1} & c_{2,g_2} \\ 0.38 & 0.68 & 0.32 & 0.62 \end{pmatrix}$$

# Example 1: Evidence $H = h_1$ (Sending Messages)



$$M_{53} = \begin{pmatrix} f_{1,g_1} & f_{1,g_2} & f_{2,g_1} & f_{2,g_2} \\ 0.2 & 0.5 & 0.4 & 0.7 \end{pmatrix}$$

$$M_{21} = \begin{pmatrix} b_{1,c_1} & b_{1,c_2} & b_{2,c_1} & b_{2,c_2} \\ 0.06 & 0.10 & 0.40 & 0.44 \end{pmatrix}$$

$$M_{41} = \begin{pmatrix} b_1 & b_2 \\ 1 & 1 \end{pmatrix}$$

$$M_{31} = \begin{pmatrix} c_{1,g_1} & c_{1,g_2} & c_{2,g_1} & c_{2,g_2} \\ 0.38 & 0.68 & 0.32 & 0.62 \end{pmatrix}$$

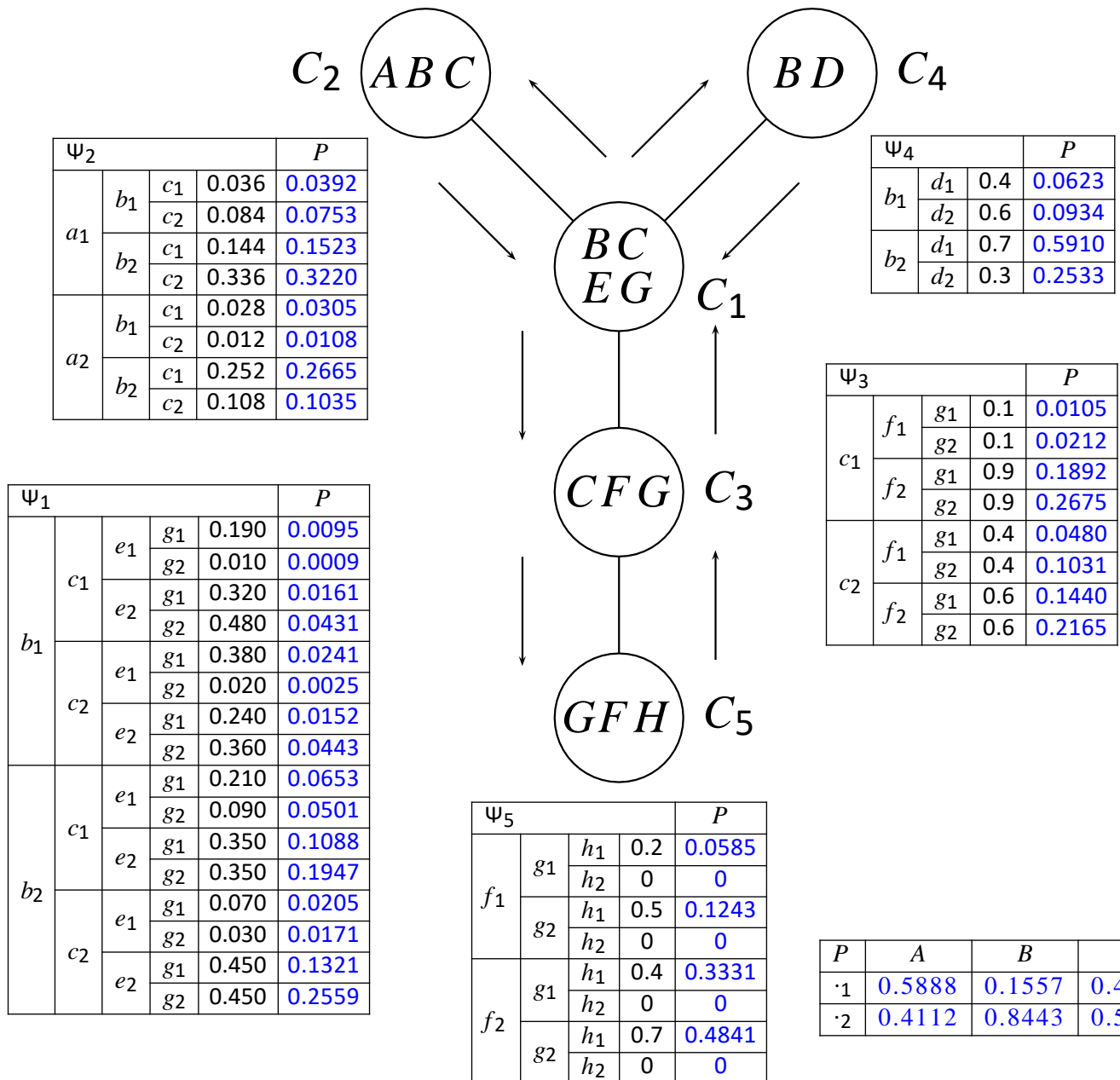
$$M_{12} = \begin{pmatrix} b_{1,c_1} & b_{1,c_2} & b_{2,c_1} & b_{2,c_2} \\ 0.527 & 0.434 & 0.512 & 0.464 \end{pmatrix}$$

$$M_{14} = \begin{pmatrix} b_1 & b_2 \\ 0.075 & 0.409 \end{pmatrix}$$

$$M_{13} = \begin{pmatrix} c_{1,g_1} & c_{1,g_2} & c_{2,g_1} & c_{2,g_2} \\ 0.254 & 0.206 & 0.290 & 0.250 \end{pmatrix}$$

$$M_{35} = \begin{pmatrix} f_{1,g_1} & f_{1,g_2} & f_{2,g_1} & f_{2,g_2} \\ 0.14 & 0.12 & 0.40 & 0.33 \end{pmatrix}$$

# Example 1: Evidence $H = h_1$ Incorporated



$$M_{53} = \begin{pmatrix} f_{1,g_1} & f_{1,g_2} & f_{2,g_1} & f_{2,g_2} \\ 0.2 & 0.5 & 0.4 & 0.7 \end{pmatrix}$$

$$M_{21} = \begin{pmatrix} b_{1,c_1} & b_{1,c_2} & b_{2,c_1} & b_{2,c_2} \\ 0.06 & 0.10 & 0.40 & 0.44 \end{pmatrix}$$

$$M_{41} = \begin{pmatrix} b_1 & b_2 \\ 1 & 1 \end{pmatrix}$$

$$M_{31} = \begin{pmatrix} c_{1,g_1} & c_{1,g_2} & c_{2,g_1} & c_{2,g_2} \\ 0.38 & 0.68 & 0.32 & 0.62 \end{pmatrix}$$

$$M_{12} = \begin{pmatrix} b_{1,c_1} & b_{1,c_2} & b_{2,c_1} & b_{2,c_2} \\ 0.527 & 0.434 & 0.512 & 0.464 \end{pmatrix}$$

$$M_{14} = \begin{pmatrix} b_1 & b_2 \\ 0.075 & 0.409 \end{pmatrix}$$

$$M_{13} = \begin{pmatrix} c_{1,g_1} & c_{1,g_2} & c_{2,g_1} & c_{2,g_2} \\ 0.254 & 0.206 & 0.290 & 0.250 \end{pmatrix}$$

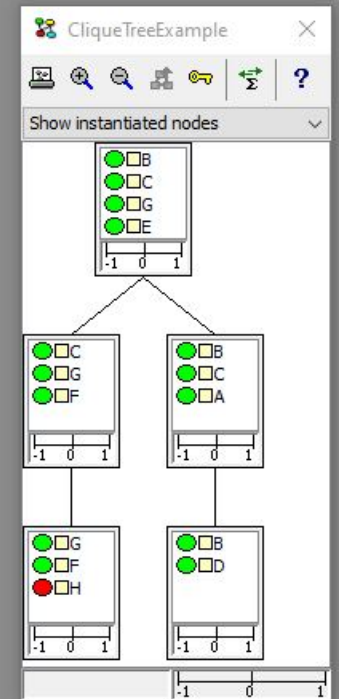
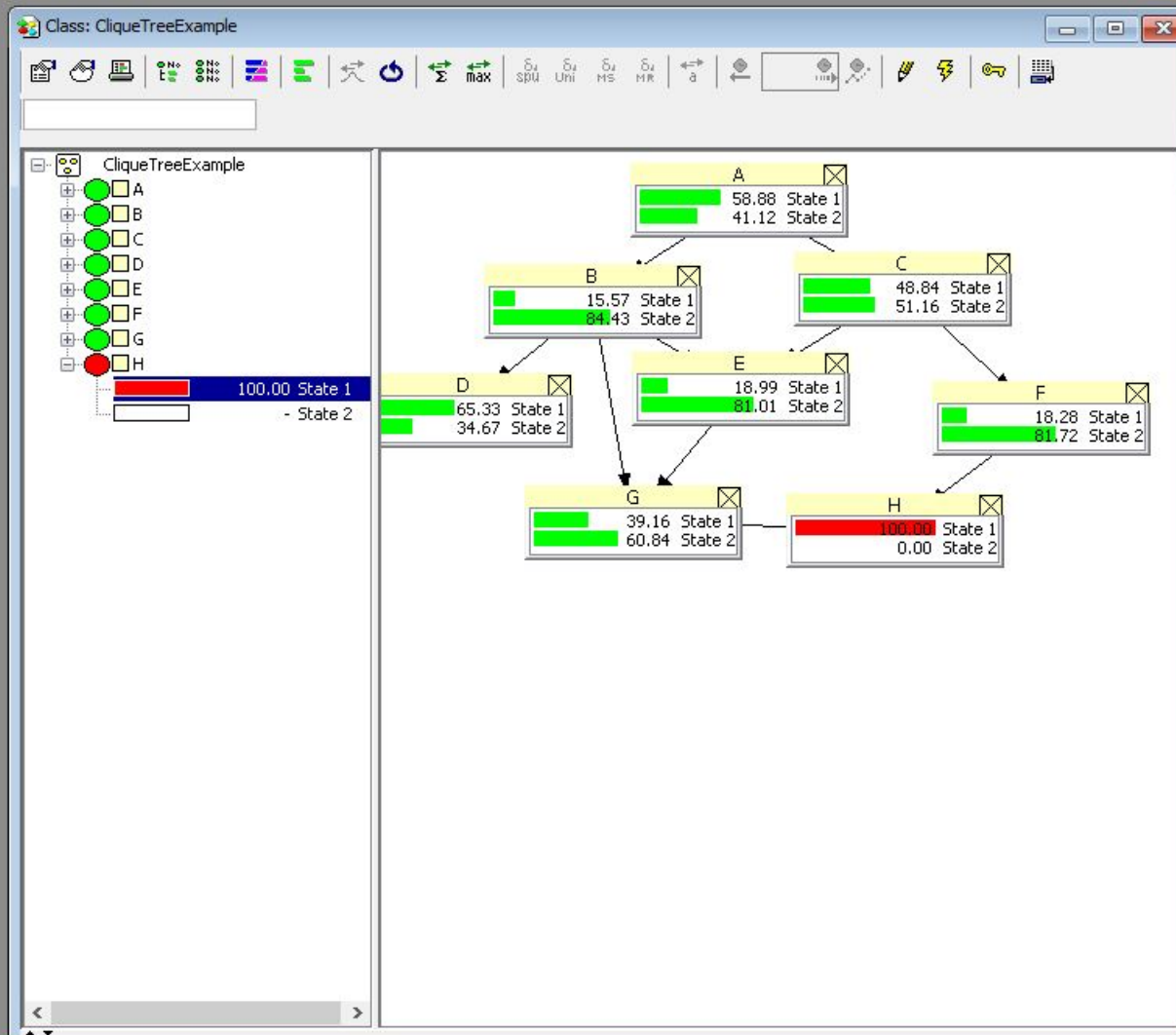
$$M_{35} = \begin{pmatrix} f_{1,g_1} & f_{1,g_2} & f_{2,g_1} & f_{2,g_2} \\ 0.14 & 0.12 & 0.40 & 0.33 \end{pmatrix}$$

$P$	A	B	C	D	E	F	G	H
$\cdot 1$	0.5888	0.1557	0.4884	0.6533	0.1899	0.1828	0.3916	1.0000
$\cdot 2$	0.4112	0.8443	0.5116	0.3467	0.8101	0.8172	0.6084	0.0000

# HUGIN's Solution

Hugin Lite 8.9

File Data Edit View Network Options Windows Wizards Help

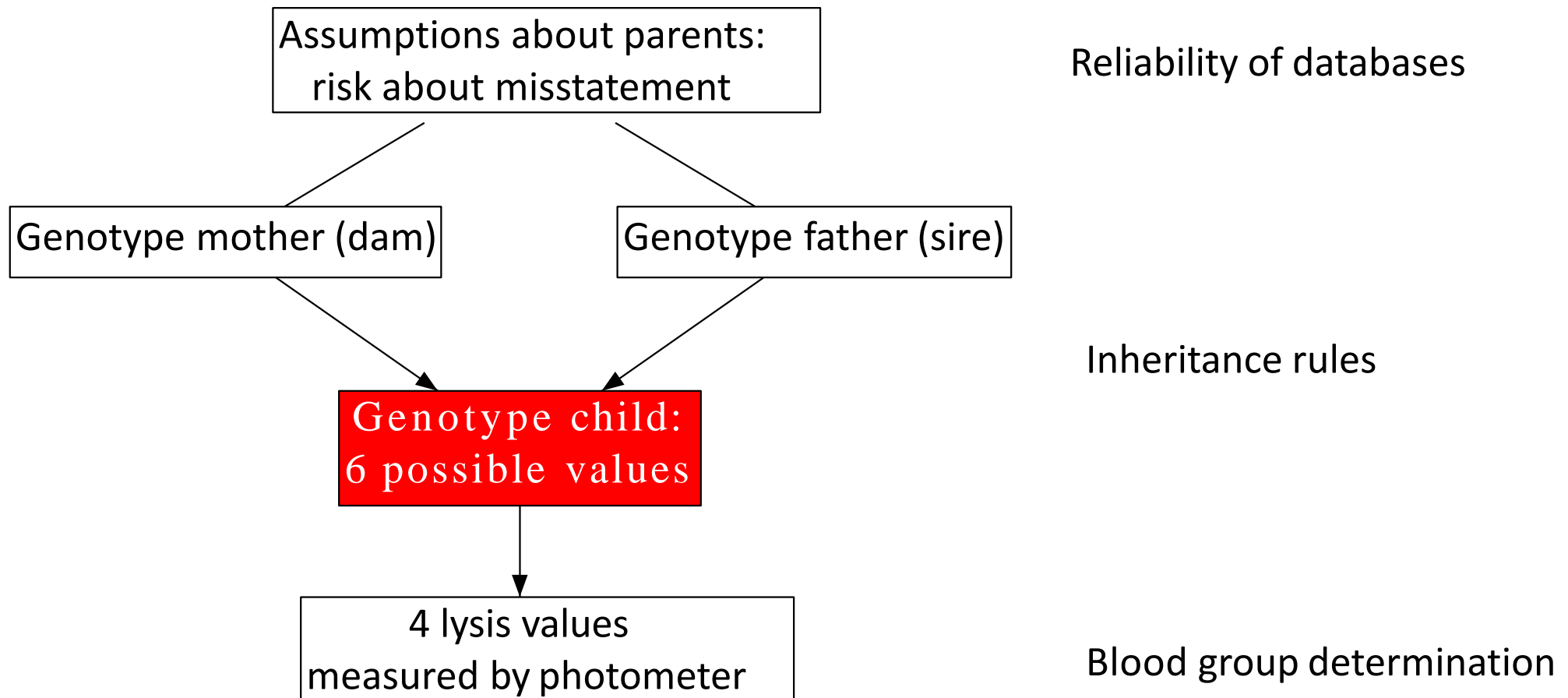


There are several exact inference methods for Bayesian Networks beside the clique tree propagation such as variable elimination or recursive conditioning. These algorithms have all complexity that is exponential with networks tree width. Exact inference is NP-hard.

In very large applications it is often useful to introduce topological structural constraints or restrictions on conditional probabilities, i.e. bounded variance algorithms.

There are also several approximate inference methods.

# Example 2: Genotype Determination of Danish Jersey Cattle



See the Paper „Blood group determination of Danish Jersey Cattle in the F-blood group system“ by Lene Kolind Rasmussen for the details.



## Example 2: Genotype Determination of Danish Jersey Cattle

Full 21-dimensional domain has  $2^6 \cdot 3^{10} \cdot 6 \cdot 8^4 = 92\,876\,046\,336$  possible states.

Bayesian network requires only 306 conditional probabilities.

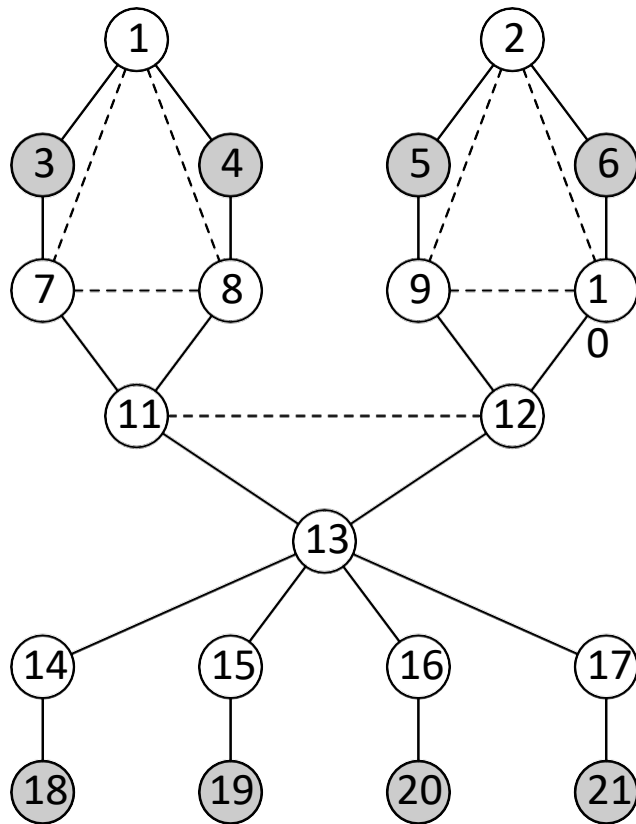
Example of a conditional probability table (attributes 2, 9, and 5):

sire correct	true sire phenogroup1	stated sire phenogroup 1		
		F1	V1	V2
yes	F1	1	0	0
yes	V1	0	1	0
yes	V2	0	0	1
no	F1	0.58	0.10	0.32
no	V1	0.58	0.10	0.32
no	V2	0.58	0.10	0.32

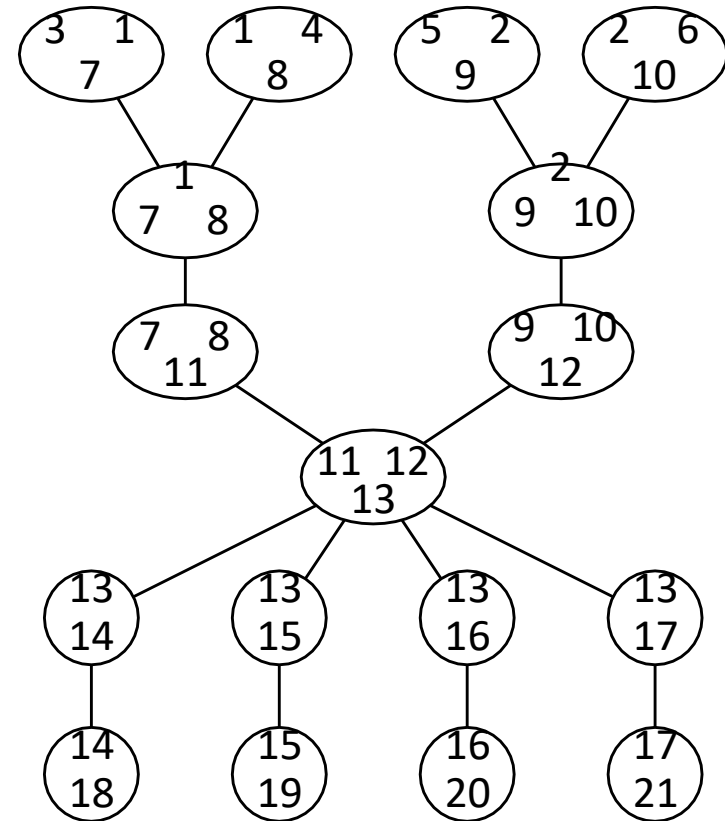
The probabilities are acquired from human domain experts or estimated from historical data.



# Example 2: Genotype Determination of Danish Jersey Cattle



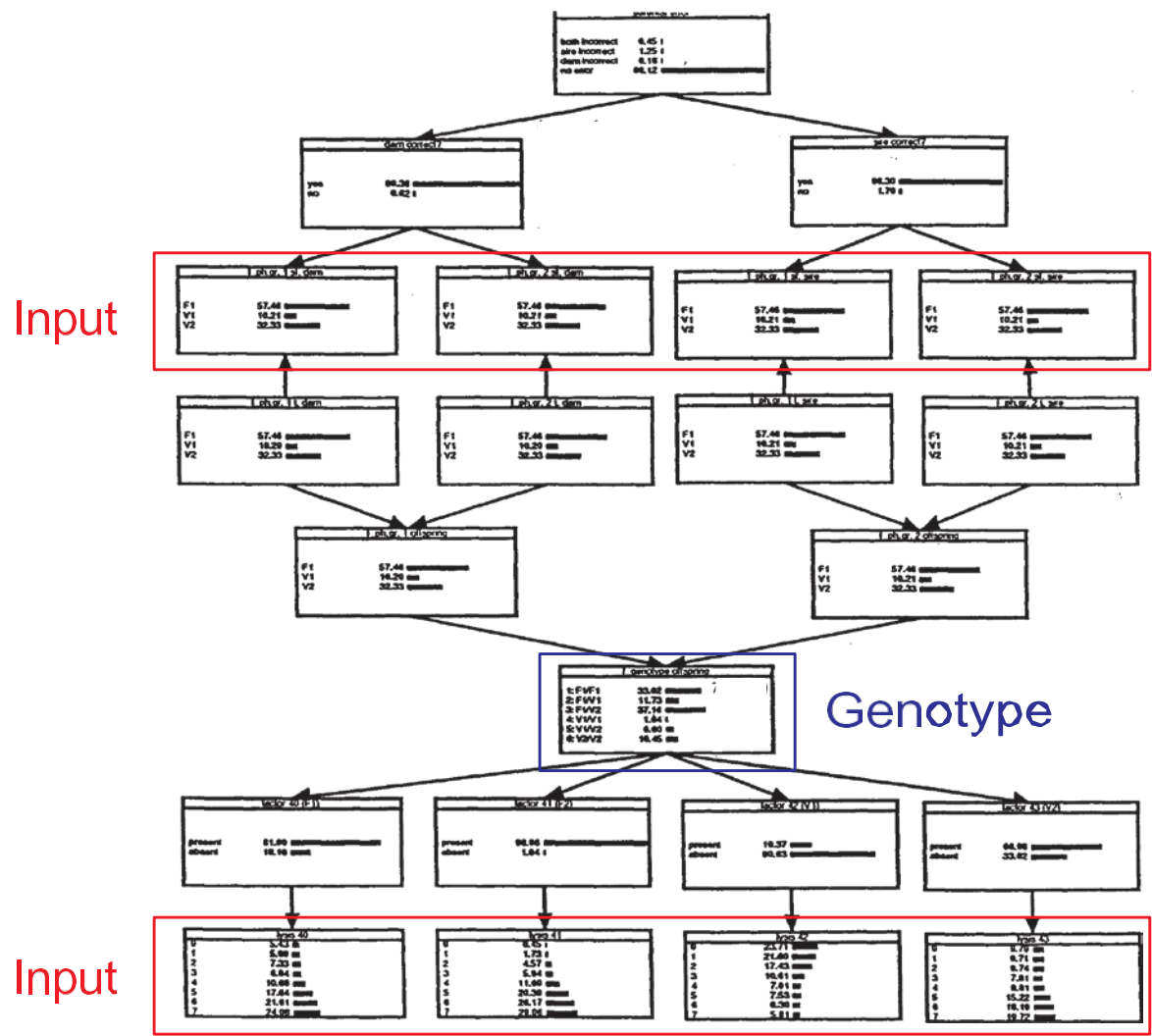
**moral graph**  
(already triangulated)



**join tree**

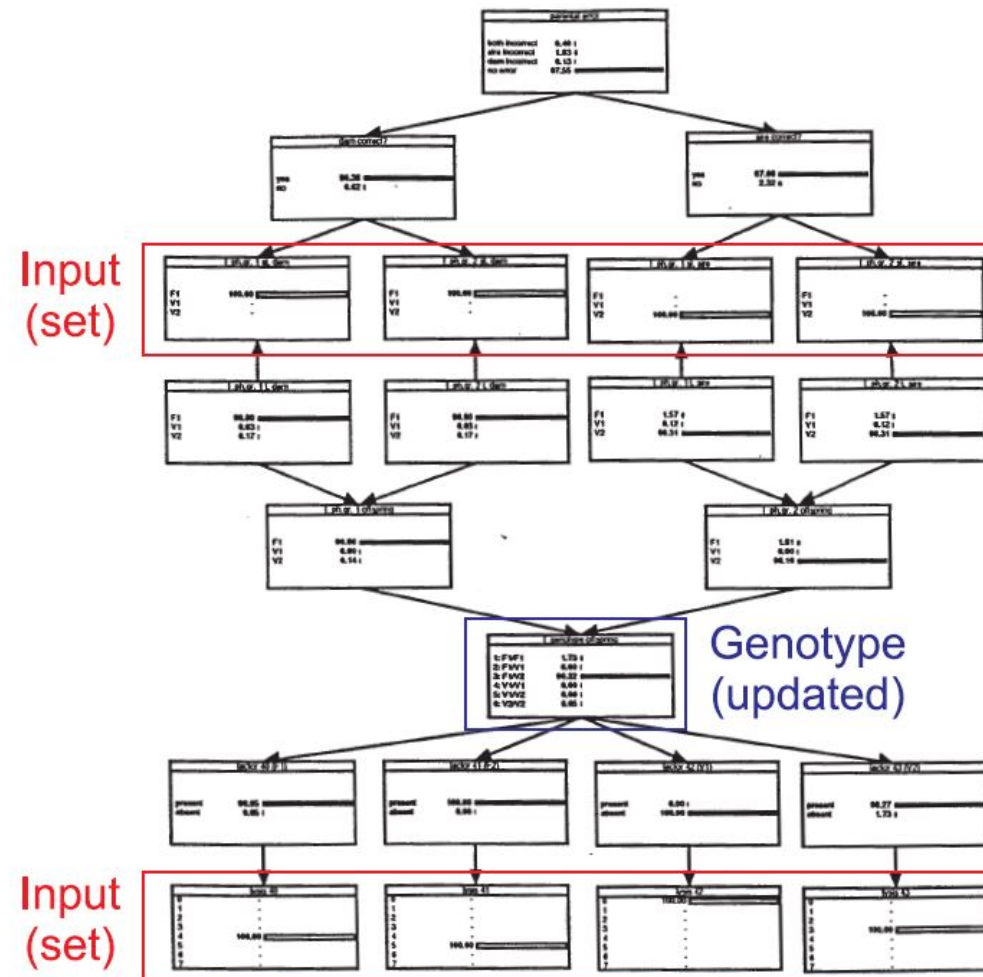
# Example 2: Genotype Determination of Danish Jersey Cattle

Marginal distributions before setting evidence:



# Example 2: Genotype Determination of Danish Jersey Cattle

Conditional distributions given evidence in the input variables:



## Example 3: Property planning - Volkswagen

Property family	Car body	Motor	Radio	Doors	Seat cover	Makeup mirror	...
Property	Hatch-back	2.8 L 150 kW Otto	Type alpha	4	Leather, Type L3	yes	...

### Complexity

- About 200 variables
- Typically 4 to 8, but up to 150 possible instances per variable
- More than  $2^{200}$  possible combinations available



## Example 3: Handling the System of Technical Rules

- 10000 Technical Rules for Item Combinations, e.g.

**IF Motor =  $m_4$  AND Heating =  $h_1$**

**THEN Generator  $\in \{g_3, g_4, g_5\}$**

- Technical Rules can be seen as Constraints, e.g. 3-dimensional relations
- The Rules are often 6-dimensional, sometimes more than 10 dimensions
- 500000 marketing oriented rules

## Example 3: Property planning

- Goals:  
Model possible (part-relevant) property combinations  
Support demand forecasts for all (part-relevant) property combinations
- Planning intervals: short-term, mid-term
- Context: Model groups, Planning intervals
- Daily: 5000 planning szenarios handled by 350 planners worldwide

**Assistant System for Handling the Planner's Knowledge  
about the Installation Rates of Property Combinations**

## Example 3: Planning Tasks

### Calculation of part demands

Compute the installation rate of a given item combination

### Simulation

Analyze customers' preferences with respect to those persons who use a navigation system in a VW Polo

### Marketing and Sales stipulation

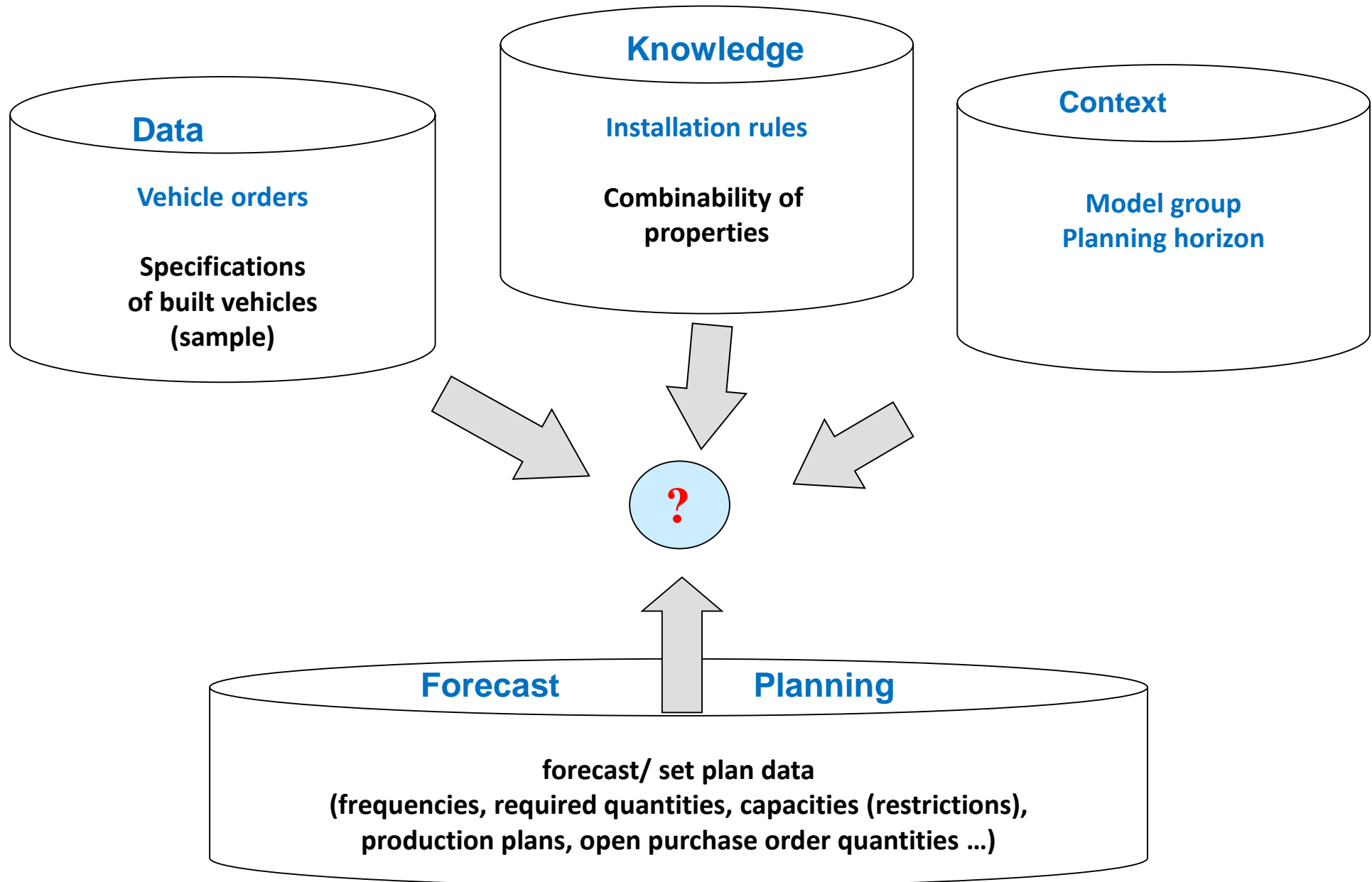
Installation rate of Navigation system increase from 20% to 30%

### Capacity Restrictions

Maximum availability of seat coverings in leather is 5000

In the language of the philosopher Gärdenfors: An agent (planner) is in a Belief State, he is using the belief change operations **Contraction (Focusing)** and **Revision**

# Example 3: Qualitative and Quantitative Information about Property Planning





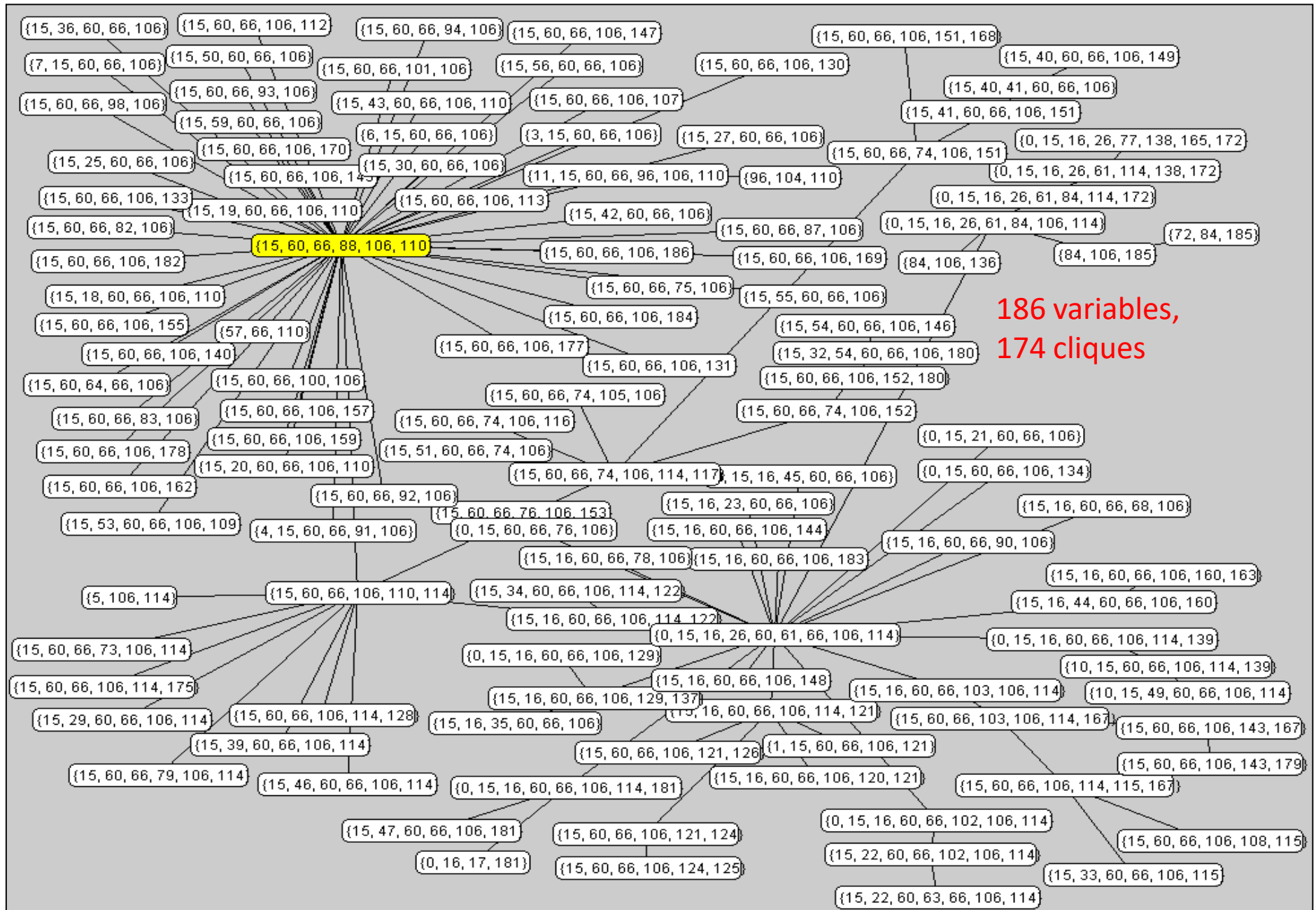
### Planners (2008)

- Explicit, Sound, Transparent Model
- Explanation of the Results
- Answers to the Questions in real time (seconds)
- Automatic Integration of New Information into the Model

### Law (since 2018)

EU's General Data Protection Regulation (GDPR) includes a **right to explanation** : "The use of AI tools should be transparent, explainable, fair, and empirically sound while fostering accountability."

# Example 3 : Markov Network for VW Bora



## Example 3 : System EPL (EigenschaftsPLANung) at VW

**Project leader: Intelligent System Consulting (PD Dr.habil. Jörg Gebhardt)**

**In worldwide use : 15 developers, 350 planners**

**Different planning responsibilities with individual workflow**

- Assessment of demand for approx. 40 planning intervals (weeks, months)
- 5000 different Markov networks in use daily

# Important Topics for Real Applications

## ***Fusion of Qualitative and Quantitative Knowledge***

Data, Rule Systems, Conditional Independence Statements, Contexts, etc.

## ***Learning Models from Data***

- Parameters (e.g. Conditional Probabilities) and Structure (e.g. DAG, Cliques)
- Model Change in the light of new Information (rules, probabilities)
- Handling Inconsistencies and Missing Values, Modelling Causalities
- Scalability, Transparency, Audability, Accountability, Accuracy,...

## ***Decision Making***

Decisions under Uncertainty, Uncertainty Quantification (Epistemic vs Aleatoric),

## ***Trustworthy Solutions of AI Solutions***

- **Ethical, Lawful, Robust (from a technical perspective and in its social environment)**
- Safety, Fairness, Non-discrimination, Privacy and Data Governance,
- Human Agency and Oversight, Societal and Environmental Well-Being...