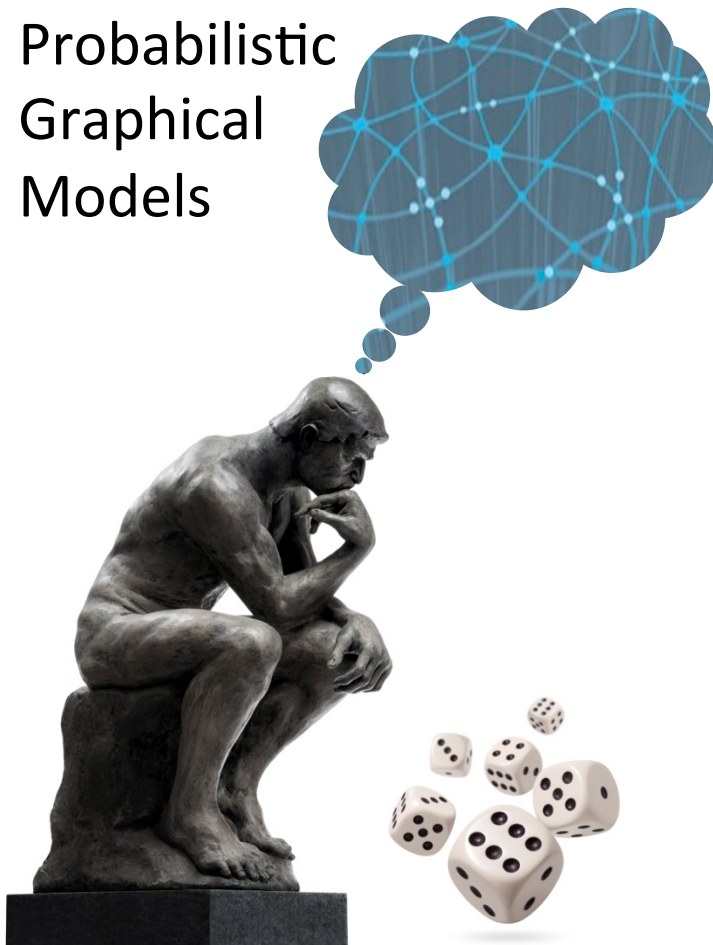


Probabilistic
Graphical
Models



Inference

MAP

Max-Sum

Exact Inference

Product \Rightarrow Summation

$$P_{\Phi}(\mathbf{x}) \propto \prod_k \phi_k(\mathbf{D}_k)$$

$$\operatorname{argmax} \prod_k \phi_k(\mathbf{D}_k)$$

log $\phi_k(\mathbf{D}_k)$

$$\operatorname{argmax} \sum_k \theta_k(\mathbf{D}_k)$$

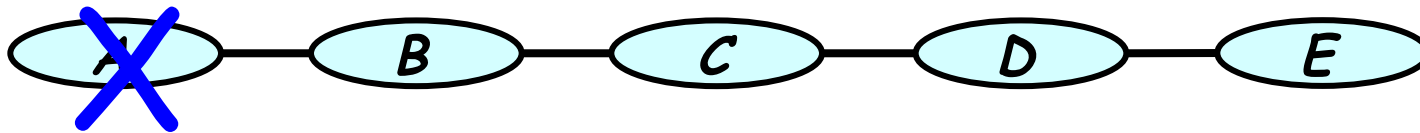
$\underbrace{\quad\quad\quad}_{\theta(X_1, \dots, X_n)}$

a ¹	b ¹	8
a ¹	b ²	1
a ²	b ¹	0.5
a ²	b ²	2



a ¹	b ¹	3
a ¹	b ²	0
a ²	b ¹	-1
a ²	b ²	1

Max-Sum Elimination in Chains



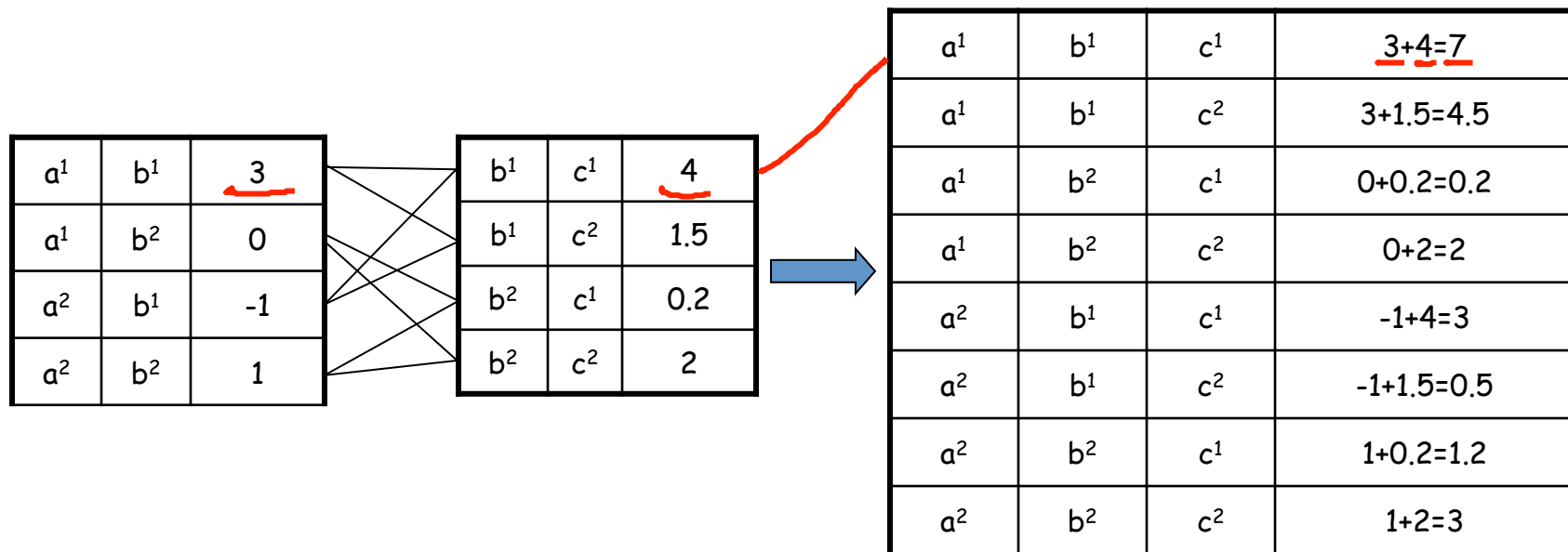
$\theta(A, B, C, D, E)$

$$\max_D \max_C \max_B \max_A (\theta_1(A, B) + \theta_2(B, C) + \theta_3(C, D) + \theta_4(D, E))$$

$$\max_D \max_C \max_B (\theta_2(B, C) + \theta_3(C, D) + \theta_4(D, E) + \max_A \theta_1(A, B))$$

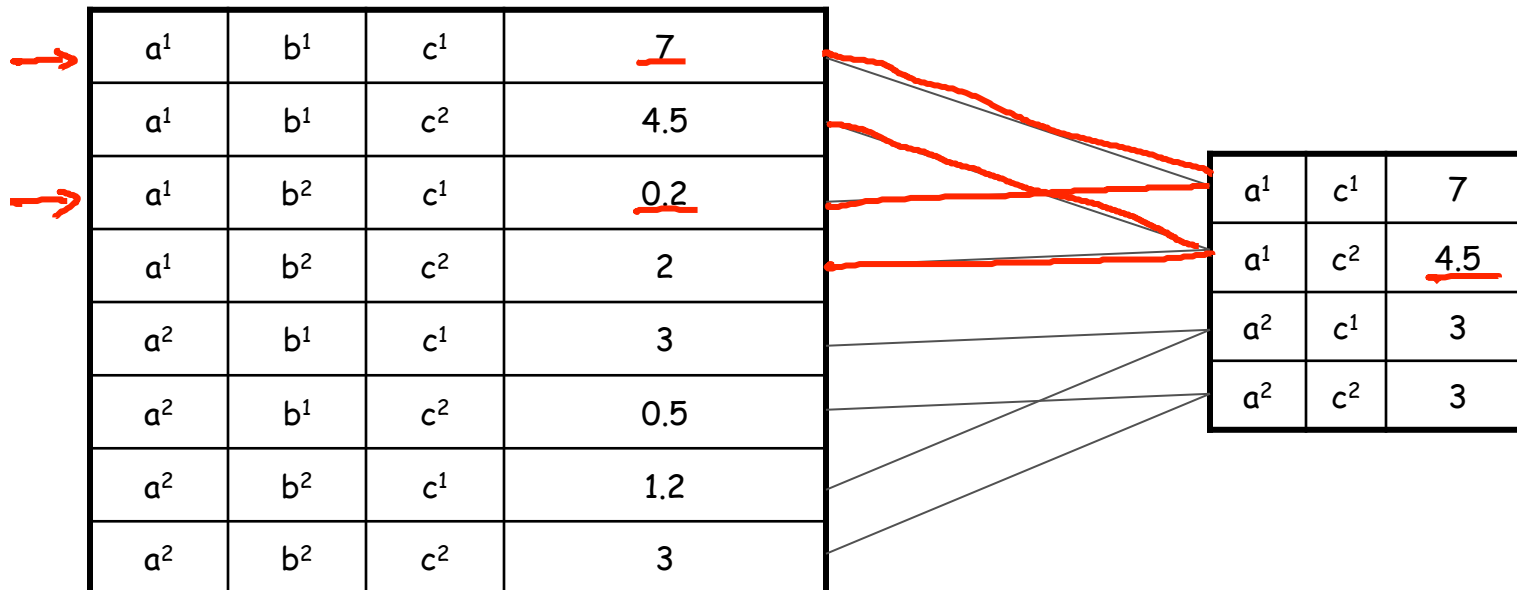
$$\max_D \max_C \max_B (\theta_2(B, C) + \theta_3(C, D) + \theta_4(D, E) + \lambda_1(B))$$

Factor Summation

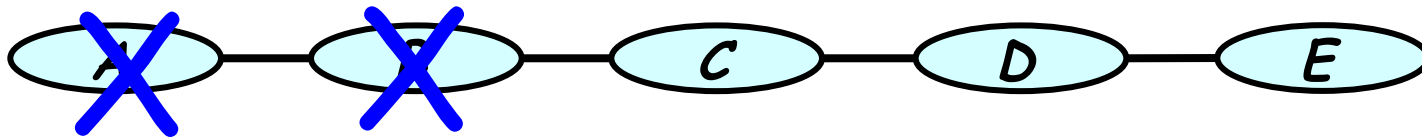


Factor Maximization

max - marginalization



Max-Sum Elimination in Chains

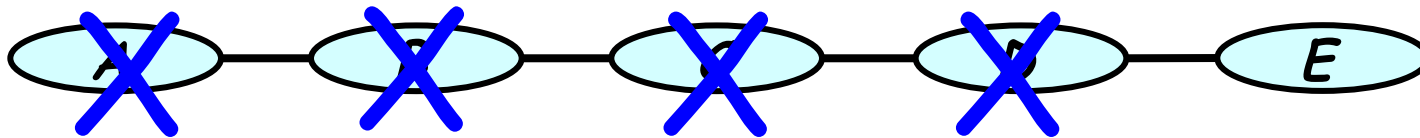


$$\max_D \max_C \max_B (\theta_2(B, C) + \theta_3(C, D) + \theta_4(D, E) + \lambda_1(B))$$

$$\max_D \max_C (\theta_3(C, D) + \theta_4(D, E) + \max_B (\theta_2(B, C) + \lambda_1(B)))$$

$$\max_D \max_C (\theta_3(C, D) + \theta_4(D, E) + \lambda_2(C))$$

Max-Sum Elimination in Chains



$$\max_D \max_C (\theta_3(C, D) + \theta_4(D, E) + \lambda_2(C))$$

$$\max_D (\theta_4(D, E) + \lambda_3(D))$$

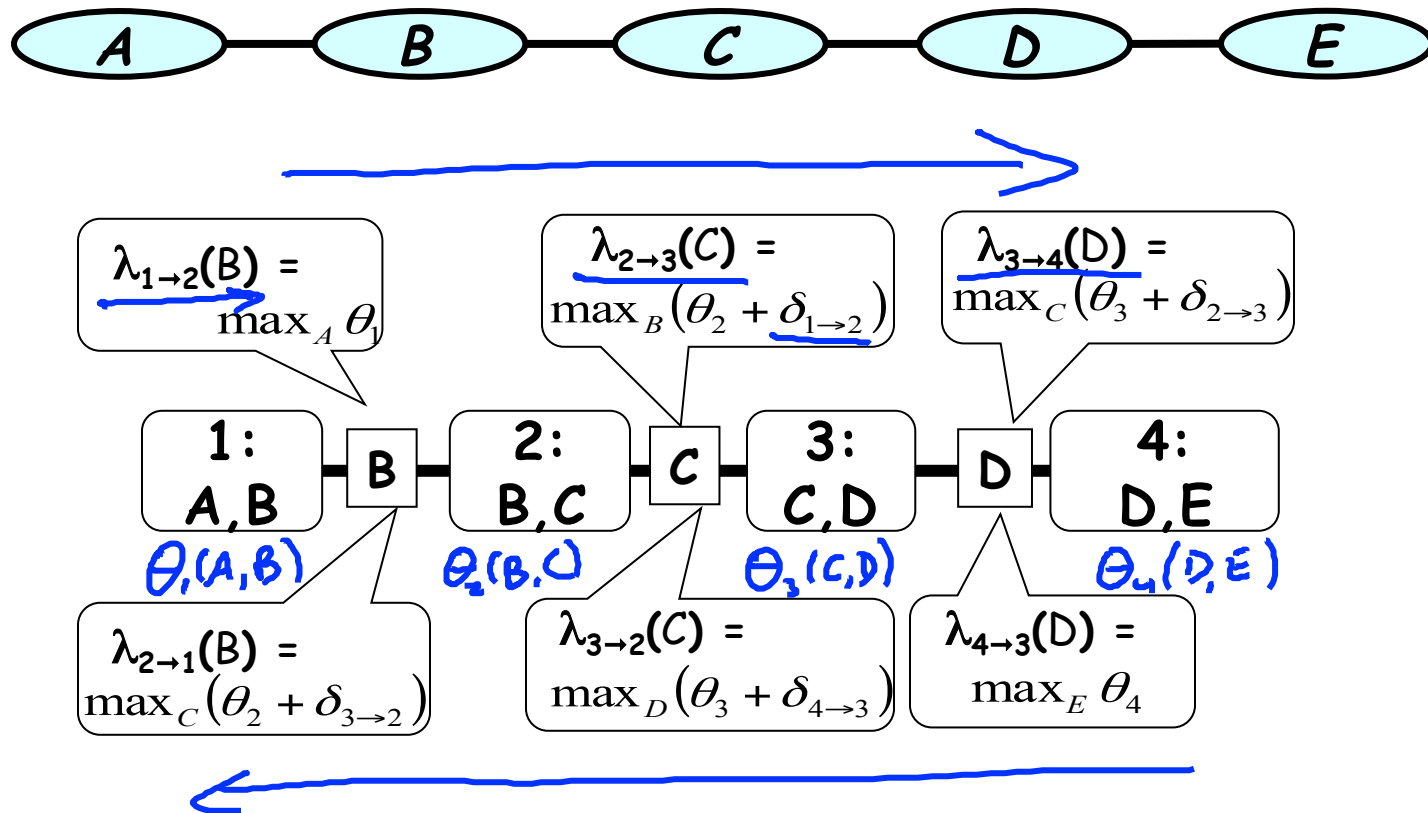
$$\lambda_4(E)$$

$$\lambda_4(e) = \max_{a,b,c,d} \Theta(a,b,c,d,e)$$

max-marginal

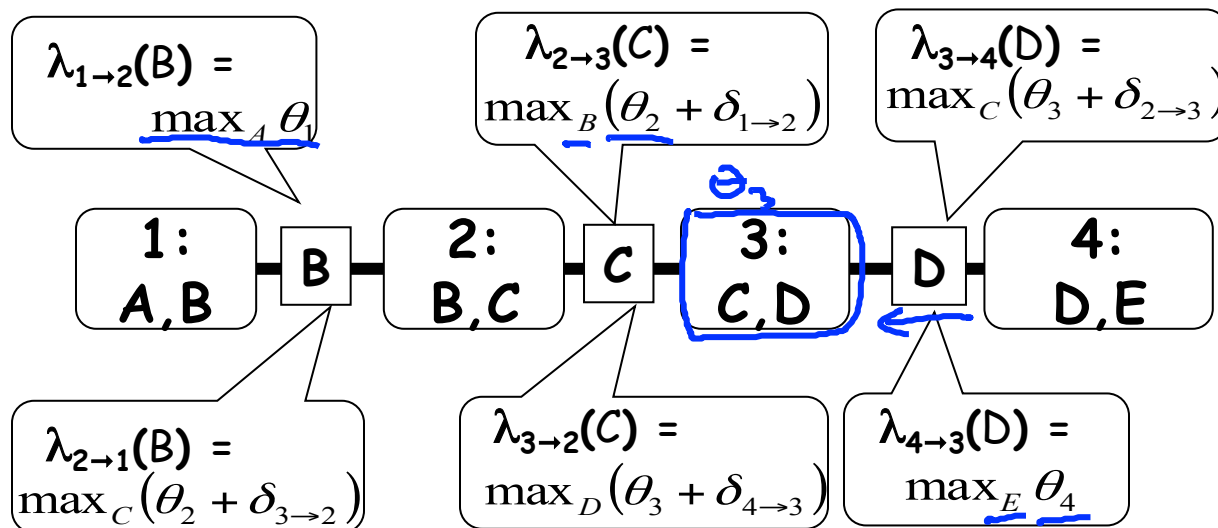
best value that
I can get if we
mandate $\bar{E}=e$

Max-Sum in Clique Trees

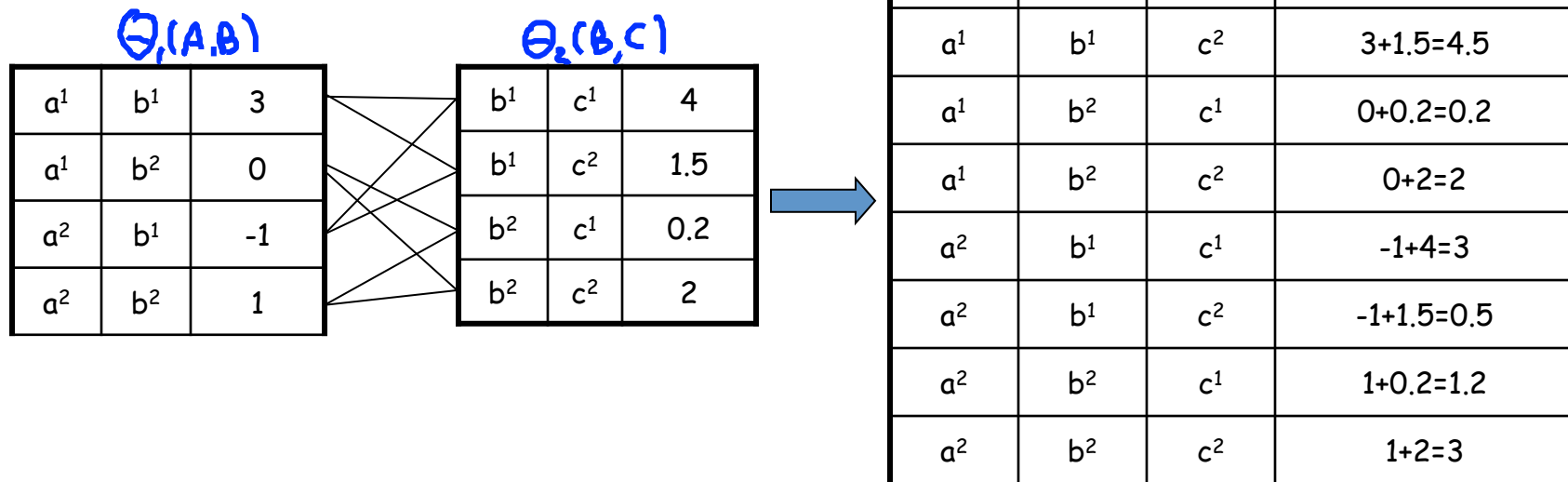
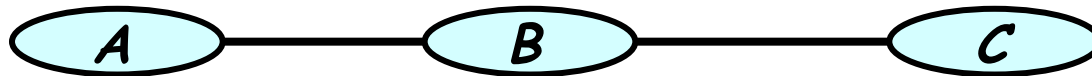


Convergence of Message Passing

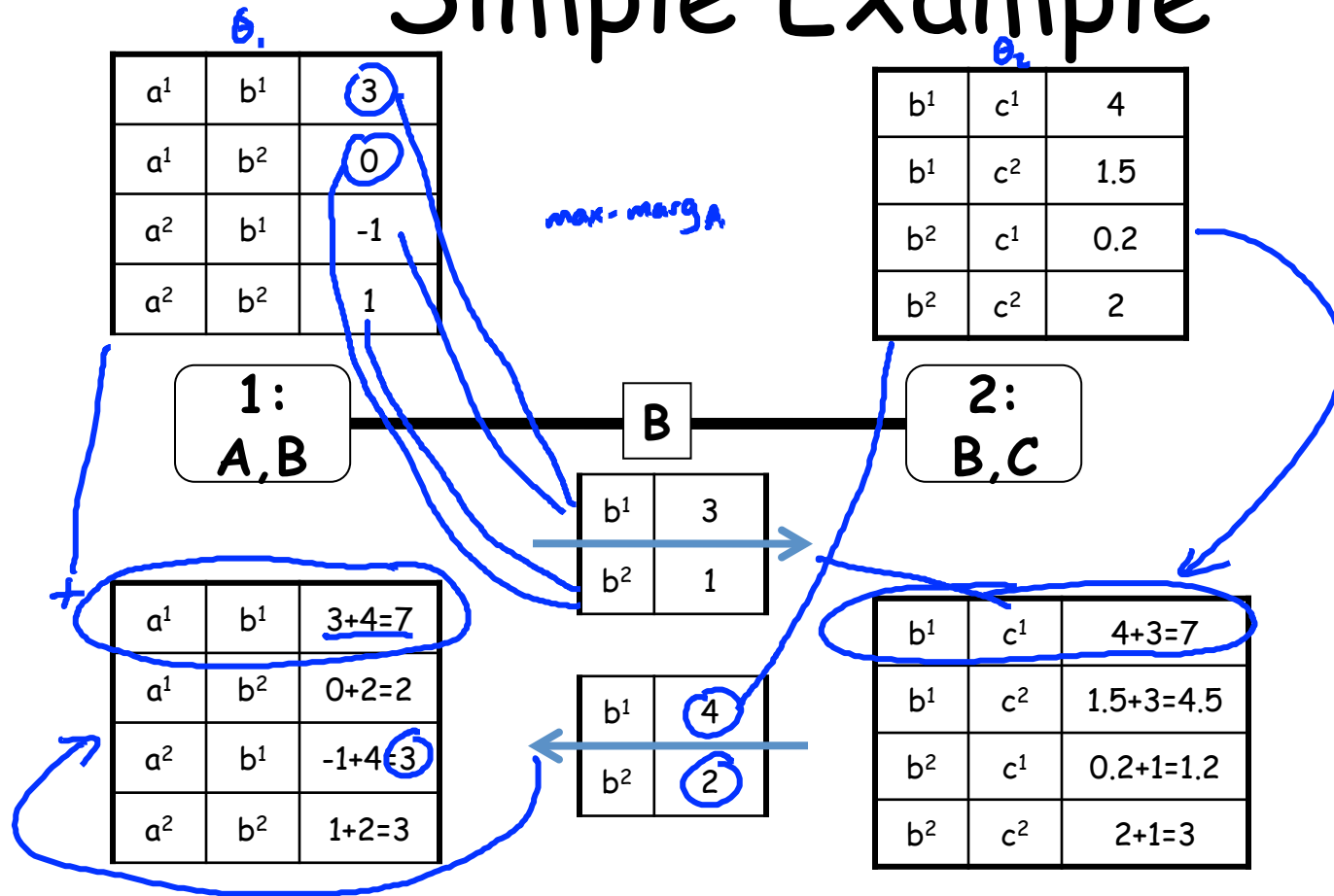
- Once C_i receives a final message from all neighbors except C_j , then $\lambda_{i \rightarrow j}$ is also final (will never change)
- Messages from leaves are immediately final



Simple Example



Simple Example



Max-Sum BP at Convergence

- Beliefs at each clique are max-marginals

$$\beta_i(C_i) = \theta_i(C_i) + \sum_k \lambda_{k \rightarrow i} \quad \text{incoming msgs}$$

$$\beta_i(\underline{C_i}) = \max_{W_i} \theta(C_i, W_i)$$

$$\underline{W_i = \{X_1, \dots, X_n\} - C_i}$$

- Calibration: cliques agree on shared variables

$$\max_{C_i - S_{i,j}} \beta_i(C_i) = \max_{C_j - S_{i,j}} \beta_j(C_j)$$

$$\beta_1 = \theta_1 + \lambda_{2 \rightarrow 1}$$

a ¹	b ¹	3+4=7
a ¹	b ²	0+2=2
a ²	b ¹	-1+4=3
a ²	b ²	1+2=3

$$b^1: 7$$

$$b^2: 3$$

$$b^1: 7$$

$$b^2: 3$$

b ¹	c ¹	4+3=7
b ¹	c ²	1.5+3=4.5
b ²	c ¹	0.2+1=1.2
b ²	c ²	2+1=3

$$\beta_2 = \theta_2 + \lambda_{1 \rightarrow 2}$$

Summary

- The same clique tree algorithm used for sum-product can be used for max-sum
- As in sum-product, convergence is achieved after a single up-down pass
- Result is a max-marginal at each clique C :
 - For each assignment c to C , what is the score of the best completion to c