

## Summary

- Max-Product Belief Propagation (BP) is a successful heuristic for finding the MAP assignment in probabilistic graphical models (GM)
- BP was recently shown to be convergent & correct in loopy GMs corresponding to classic combinatorial optimization problems
- A necessary condition for BP to succeed in such problems is that the LP relaxation of the MAP assignment problem be tight
- Tightness is **not** a sufficient condition however, and we explore why BP fails even when the LP is tight
- We focus on the classic Max Weight Matching problem and propose a novel graphical transformation that forces BP to converge when the LP relaxation of the matching problem is tight
- This is an important step towards designing BP algorithms guaranteed to recover the LP solution

## Max-Product for Matching

### Graphical Model Formulation (GM-0):

$$\max_x \prod_{e \in E} \exp(w_e x_e) \prod_{i \in V} \psi_i(x_i) \prod_{C \in \mathcal{C}} \psi_C(x_C)$$

$$\psi_i(x_i) = \begin{cases} 1 & \text{if } \sum_{e \in \delta(i)} x_e \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\psi_C(x_C) = \begin{cases} 1 & \text{if } \sum_{e \in E(C)} x_e \leq \frac{|C|-1}{2} \\ 0 & \text{otherwise} \end{cases}$$

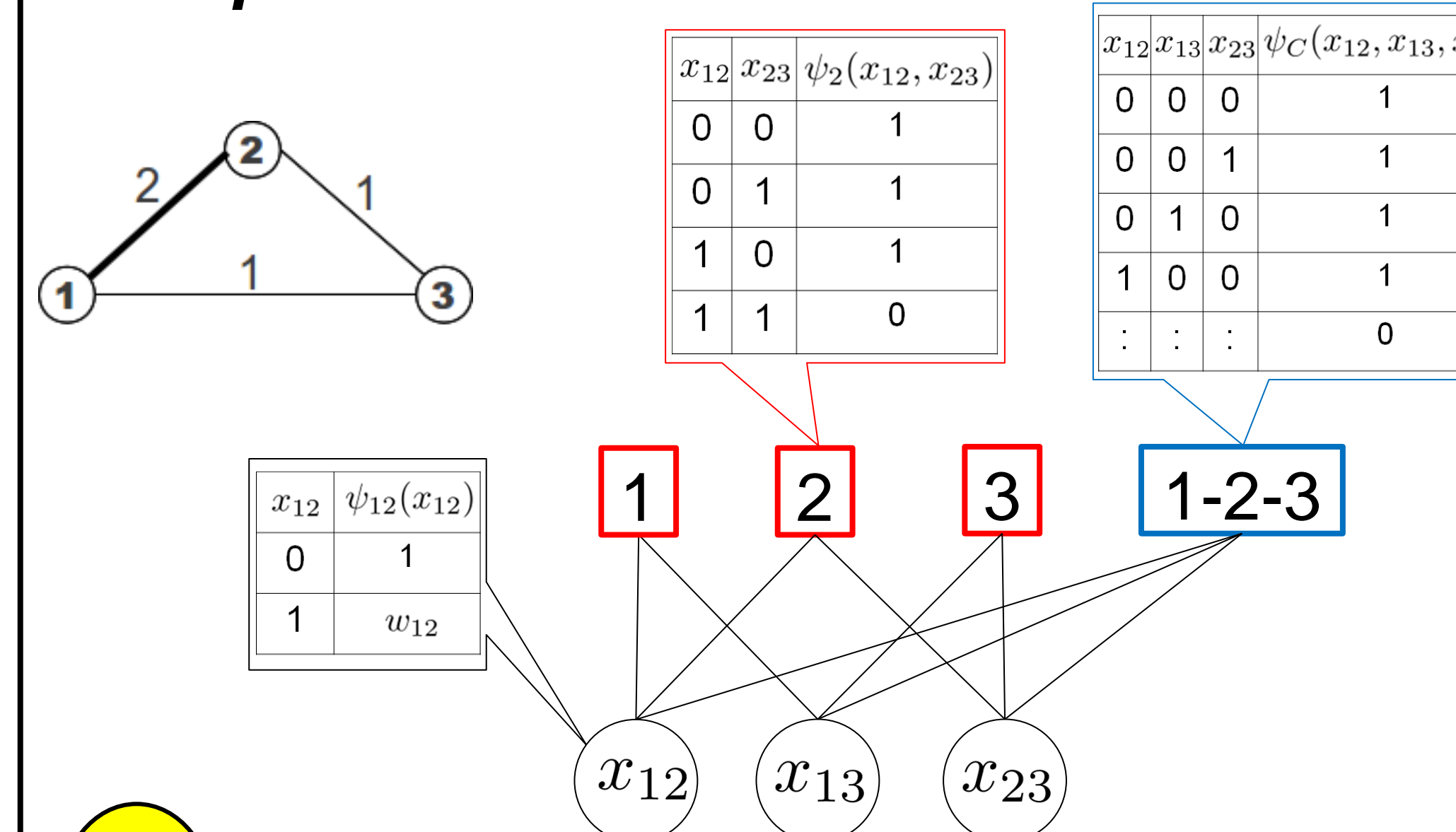
### Corresponding LP-Relaxation (C-LP):

$$\max \sum_{e \in E} w_e x_e$$

$$\text{s.t. } \sum_{e \in \delta(i)} x_e \leq 1, \forall i \in V \quad x_e \in [0, 1]$$

$$\sum_{e \in E(C)} x_e \leq \frac{|C|-1}{2}, \forall C \in \mathcal{C} \leftarrow \text{non-intersecting, odd-sized cycles}$$

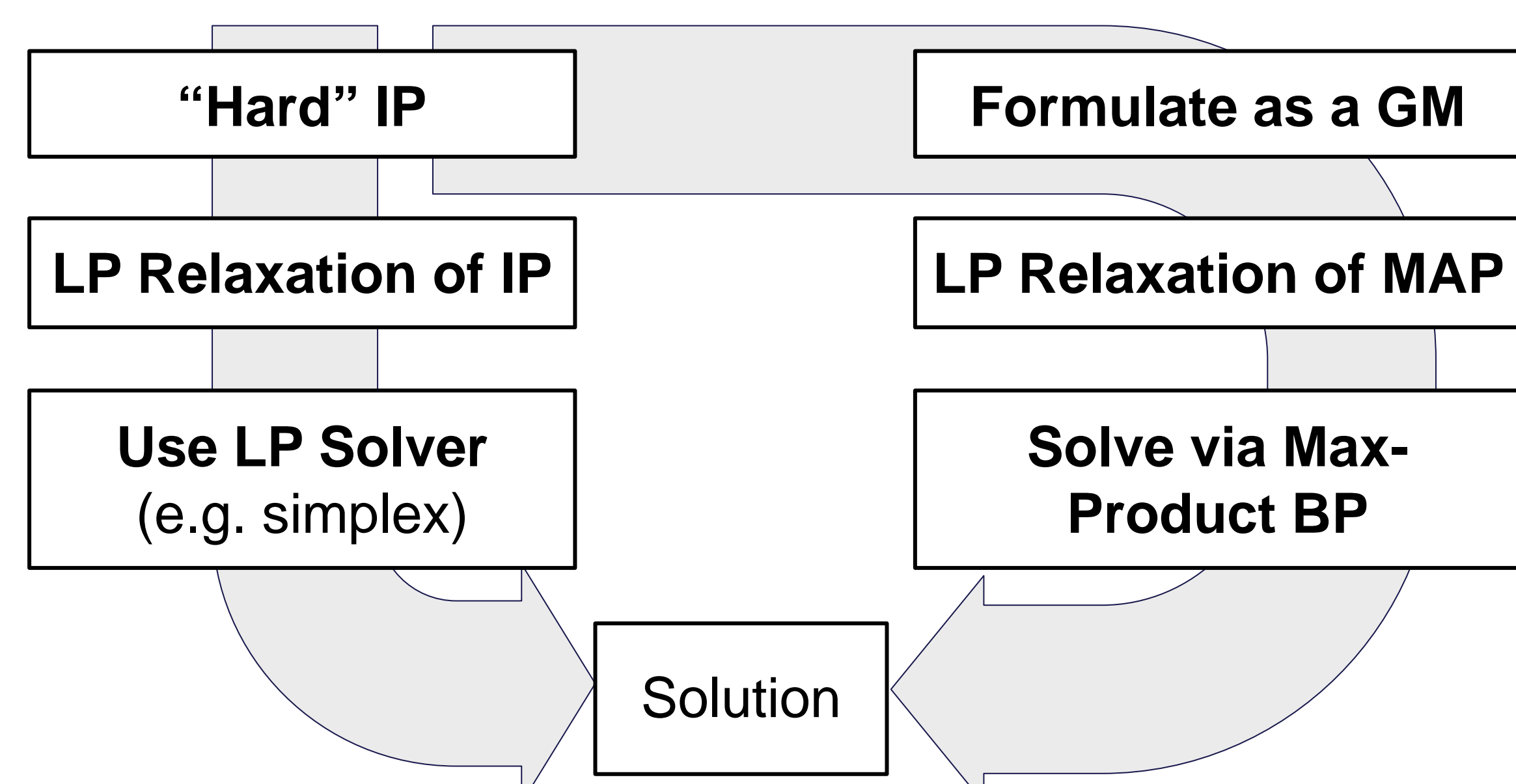
### Example:



Max-Product BP doesn't converge even though corresponding LP, C-LP, is tight!

	Iteration Number					
	0	1	2	3	4	5
Variable-to-Factor Messages:	$x_{12} \rightarrow 1$	0	-2	0	-2	0
	$x_{12} \rightarrow 2$	0	-2	0	-2	0
	$x_{13} \rightarrow 1$	0	-1	2	-1	2
	$x_{23} \rightarrow 2$	0	-1	2	-1	2
	$x_{23} \rightarrow 3$	0	-1	3	-1	3
Factor-to-Variable Messages:	$1 \rightarrow x_{12}$	0	0	1	0	1
	$2 \rightarrow x_{12}$	0	0	1	0	1
	$1 \rightarrow x_{13}$	0	0	2	0	2
	$3 \rightarrow x_{13}$	0	0	1	0	1
	$2 \rightarrow x_{23}$	0	0	2	0	2
Edge Beliefs:	$x_{12}$	-2	-2	1	-2	1
	$x_{13}$	-1	-1	4	-1	4
	$x_{23}$	-1	-1	4	-1	4

## Max-Product BP as an LP Solver



## Graphical Transformation

- Sanghavi, Malioutov & Willsky showed that BP is convergent and correct if C-LP with  $\mathcal{C} = \emptyset$  is tight (and unique)
- We "fix" BP in situations where C-LP is tight, but  $\mathcal{C} \neq \emptyset$

### New Graphical Model Formulation (GM-1):

$$\max_y \prod_{e \in E'} \exp(w'_e y_e) \prod_{i \in V'} \psi_i(y_i) \prod_{C \in \mathcal{C}} \psi_C(y_C)$$

$$\psi_C(y_C) = \begin{cases} 0 & \text{if } \sum_{e \in \delta(i_C)} y_e > |C| - 1 \\ 0 & \text{if } \sum_{j \in V(C)} (-1)^{d_C(j,e)} y_{i_C,j} \notin \{0, 2\} \text{ for an } e \in E(C) \\ 1 & \text{otherwise} \end{cases}$$

$$w'_e = \begin{cases} \frac{1}{2} \sum_{\tilde{e} \in E(C)} (-1)^{d_C(j,\tilde{e})} w_{\tilde{e}} & \text{if } e = (i_C, j) \text{ for some } C \in \mathcal{C} \\ w_e & \text{otherwise} \end{cases}$$



### Main Result:

If the solution of C-LP is integral and unique, then BP on the new GM converges to the corresponding MAP assignment  $y^*$  and the max weight matching  $x^*$  is recovered as:

$$x_e^* = \begin{cases} \frac{1}{2} \sum_{j \in V(C)} (-1)^{d_C(j,e)} y_{i_C,j}^* & \text{if } e = (i_C, j) \text{ for some } C \in \mathcal{C} \\ y_e^* & \text{otherwise} \end{cases}$$

- Proof utilizes the computation tree technique to establish a contradiction
- Each variable is adjacent to at most 2 factor nodes in the new GM
- This 'degree-two' condition is crucial to proof of convergence & correctness

## Max Weight Matching Problem

Matching is a subset of  $E$  w/ at most 1 edge adjacent to each  $V$

### Integer Program:

$$\max \sum_{e \in E} w_e x_e$$

$$\text{s.t. } \sum_{e \in \delta(i)} x_e \leq 1, \forall i \in V$$

$$x_e \in \{0, 1\}$$

### LP-Relaxation:

$$\max \sum_{e \in E} w_e x_e$$

$$\text{s.t. } \sum_{e \in \delta(i)} x_e \leq 1, \forall i \in V$$

$$x_e \in [0, 1]$$

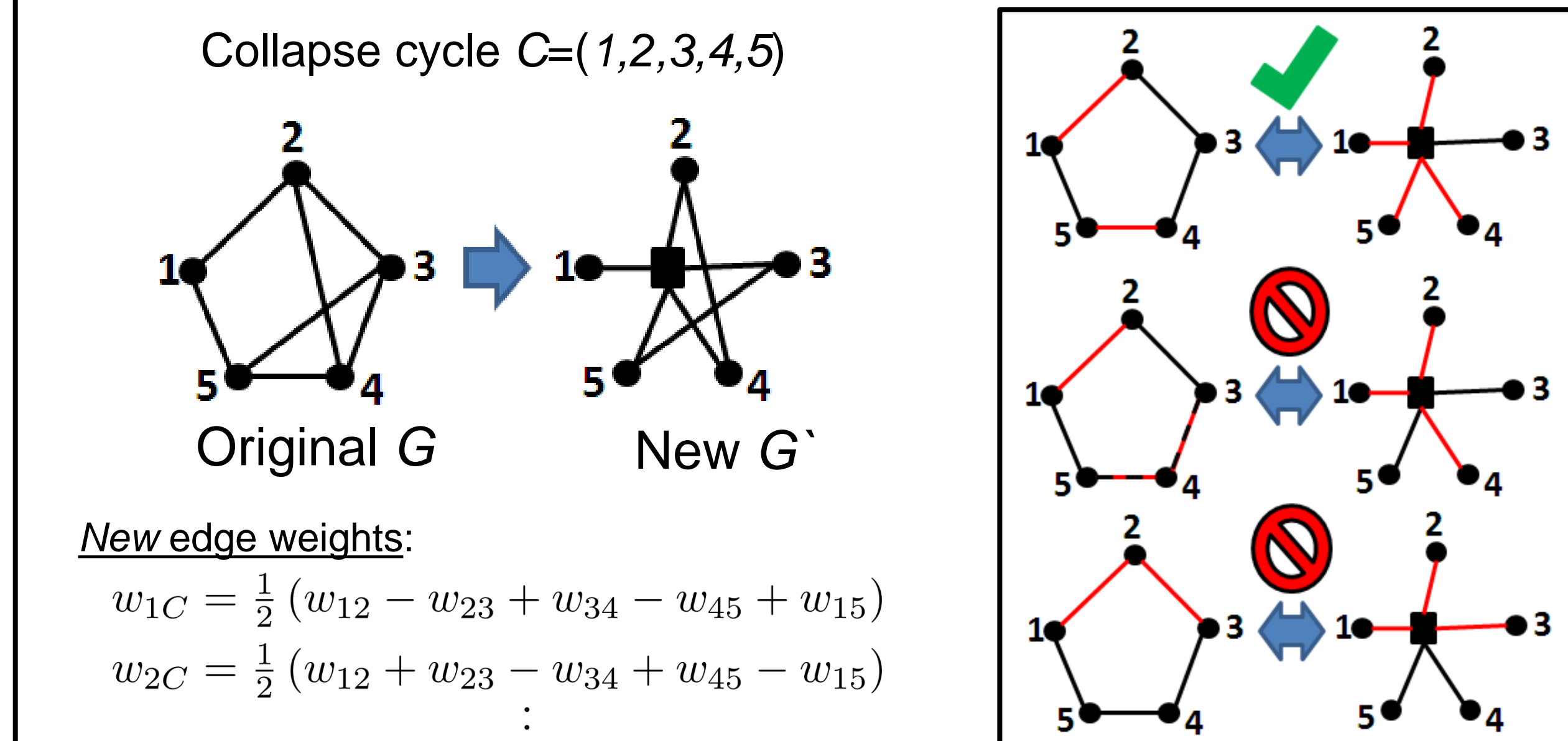
$$\sum_{e \in E(S)} x_e \leq \frac{|S|-1}{2}, \forall S \in \mathcal{S}$$

Edmonds' Blossom Constraints

- LP-Relaxation is **tight** when cut constraints for all odd-sized subsets,  $\mathcal{S}$ , have been added

- Chandrasekaran et al. 2012, showed that # of cuts,  $\mathcal{S}$ , is polynomial
- We will consider sets  $\mathcal{C}$  of non-intersecting, odd-sized cycles

### Example:



### Cutting-Plane BP Algorithm:

- Initialize  $\mathcal{C} = \emptyset$
- Run max-product BP for  $T$  iterations
- For each edge  $e$ :  $y_e = \begin{cases} 1 & \text{if } n_e^T[1] > n_e^T[0] \text{ and } n_e^{T-1}[1] > n_e^{T-1}[0] \\ 0 & \text{if } n_e^T[1] < n_e^T[0] \text{ and } n_e^{T-1}[1] < n_e^{T-1}[0] \\ 1/2 & \text{otherwise} \end{cases}$
- Recover  $x$  from  $y$  and terminate if  $x \notin \{0, 1/2, 1\}$
- if  $x_e \in \{0, 1\}$  then stop and output solution; else if can find a non-intersecting odd-sized cycle  $C$  then add it to  $\mathcal{C}$  and go to step 2. else terminate

### Variable-to-Factor Message:

$$m_{e \rightarrow \alpha}^{t+1}(x_e) = \psi_e(x_e) \prod_{\alpha' \in N(e) \setminus \alpha} m_{\alpha' \rightarrow e}^t(x_e)$$

### Factor-to-Variable Message:

$$m_{\alpha \rightarrow e}^{t+1}(x_e) = \max_{x_\alpha \setminus x_e} \left[ \psi_\alpha(x_\alpha) \prod_{e' \in N(\alpha) \setminus e} m_{e' \rightarrow \alpha}^t(x_{e'}) \right]$$

Edge Belief:  $\eta_e^t(x_e) = \psi_e(x_e) \prod_{\alpha \in N(e)} m_{\alpha \rightarrow e}^t(x_e)$