

# The Bethe Partition Function and the SPA for Factor Graphs based on Homogeneous Real Stable Polynomials

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## Main results

Consider a **standard factor graph (S-FG)**  $N$  where **each local function** is defined based on a (possibly different) **multi-affine homogeneous real stable** (MAHRS) polynomial.

Then we prove that

1. The **projection** of the **local marginal polytope** (LMP) on the **edges** in  $N$  equals the **convex hull** of the set of **valid configurations**  $\text{conv}(\mathcal{C})$ .
2. For the **typical** case where the S-FG has a **sum-product algorithm (SPA) fixed point** consisting of **positive-valued messages only**, the SPA finds the value of the **Bethe partition function**  $Z_B(N)$  **exponentially fast**.
3. The **Bethe free energy function**  $F_B$  has some **convexity properties**.

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# An introductory example

Consider the set of all **binary  $3 \times 3$  matrices**.

We want to know the number of **binary  $3 \times 3$  matrices** with **row sums** and **column sums** equaling **two**.

The following are **example binary  $3 \times 3$  matrices**:

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix} \quad \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \end{pmatrix} \quad \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{pmatrix}.$$

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$$\underbrace{\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{pmatrix}}_{\times}, \quad \underbrace{\begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \end{pmatrix}}_{\checkmark}, \quad \underbrace{\begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{pmatrix}}_{\checkmark}.$$

The number of such matrices is **3!**.

## An introductory example

$$\begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \end{pmatrix}, \quad \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 0 \end{pmatrix}.$$

- 
- ▶ These binary matrices can be viewed as **binary contingency tables** of size  $3 \times 3$  with **row sums** and **column sums** equaling **two**.
  - ▶ The number of such **binary contingency tables** is  $3!$ .

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# Setup

## Definition

1.  $[n] \triangleq \{1, 2, \dots, n\}$  for  $n \in \mathbb{Z}_{\geq 1}$  and  $[m] \triangleq \{1, 2, \dots, m\}$  for  $m \in \mathbb{Z}_{\geq 1}$ .
2.  $\mathbf{x} = (x(i, j))_{i \in [n], j \in [m]}$ : a  **$\{0, 1\}$ -valued matrix** of size  $n \times m$ .
3. For the  **$i$ -th row**  $\mathbf{x}(i, :)$ , we introduce an integer  $r_i$  and impose a **constraint** on the **row sum**:

$$\mathcal{X}_{r_i} = \left\{ \mathbf{x}(i, :) \left| \sum_{j \in [m]} x(i, j) = r_i \right. \right\}.$$

4. For the  **$j$ -th column**  $\mathbf{x}(:, j)$ , we introduce an integer  $c_j$  and impose a **constraint** on the **column sum**:

$$\mathcal{X}_{c_j} = \left\{ \mathbf{x}(:, j) \left| \sum_{i \in [n]} x(i, j) = c_j \right. \right\}.$$

# Setup

## Definition

5. The set of **valid configurations** is defined to be

$$\mathcal{C} \triangleq \left\{ \mathbf{x} \in \{0, 1\}^{n \times n} \mid \begin{array}{l} \mathbf{x}(i, :) \in \mathcal{X}_{r_i}, \forall i \in [n], \\ \mathbf{x}(:, j) \in \mathcal{X}_{c_j}, \forall j \in [m] \end{array} \right\},$$

the set of **binary matrices** such that the  **$i$ -th row sum** is  $r_i$  and the  **$j$ -th column sum** is  $c_j$ .

6. We want to compute the number of the **valid configurations**  $|\mathcal{C}|$ .

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# Graphical-model-based approximation method

## Main idea

1. Define a **standard factor graph (S-FG)**  $N$  whose partition function equals

$$Z(N) = |\mathcal{C}|.$$

2. Run the **sum product algorithm (SPA)**, a.k.a. **belief propagation (BP)**, on the S-FG  $N$  to compute the **Bethe approximation of  $|\mathcal{C}|$** , denoted by  $Z_B(N)$ .

# Graphical-model-based approximation method

## Example

Consider  $n = m = 3$  and  $r_i = c_j = 2$ , i.e.,  $\mathbf{x} \in \{0, 1\}^{3 \times 3}$ .

The  $i$ -th row  $\mathbf{x}(i, :) \in \mathcal{X}_{r_i}$  and the  $j$ -th column  $\mathbf{x}(:, j) \in \mathcal{X}_{c_j}$ , where  
 $\mathcal{X}_{r_i} = \{(1, 1, 0), (0, 1, 1), (1, 0, 1)\}$ ,  $\mathcal{X}_{c_j} = \{(1, 1, 0)^T, (0, 1, 1)^T, (1, 0, 1)^T\}$ .

### 1. The local functions:

$$f_{l,i}(\mathbf{x}(i, :)) \triangleq \begin{cases} 1 & \text{if } \mathbf{x}(i, :) \in \mathcal{X}_{r_i} \\ 0 & \text{otherwise} \end{cases}, \quad f_{r,j}(\mathbf{x}(:, j)) \triangleq \begin{cases} 1 & \text{if } \mathbf{x}(:, j) \in \mathcal{X}_{c_j} \\ 0 & \text{otherwise} \end{cases}.$$

### 2. The support of the local functions:

$$\mathcal{X}_{f_{l,i}} \triangleq \{\mathbf{x}(i, :) \in \{0, 1\}^3 \mid f_{l,i}(\mathbf{x}(i, :)) > 0\} = \mathcal{X}_{r_i},$$
$$\mathcal{X}_{f_{r,j}} \triangleq \{\mathbf{x}(:, j) \in \{0, 1\}^3 \mid f_{r,j}(\mathbf{x}(:, j)) > 0\} = \mathcal{X}_{c_j}.$$

# Graphical-model-based approximation method

## 3. The $\{0, 1\}$ -valued **global function**:

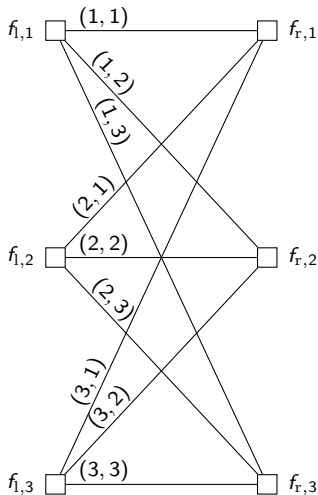
$$\begin{aligned} g(\mathbf{x}) &\triangleq f_{l,1}(x(1,1), x(1,2), x(1,3)) \\ &\quad \cdot f_{l,2}(x(2,1), x(2,2), x(2,3)) \\ &\quad \cdots f_{r,2}(x(1,2), x(2,2), x(3,2)) \\ &\quad \cdot f_{r,3}(x(1,3), x(2,3), x(3,3)). \end{aligned}$$

The **previously defined** set of **valid configurations** is equal to the **support** of the global function:

$$\mathcal{C} = \{\mathbf{x} \in \{0, 1\}^{3 \times 3} \mid g(\mathbf{x}) > 0\}.$$

## 4. The **partition function**:

$$Z(N) \triangleq \sum_{\mathbf{x} \in \{0,1\}^{3 \times 3}} g(\mathbf{x}) = |\mathcal{C}|.$$



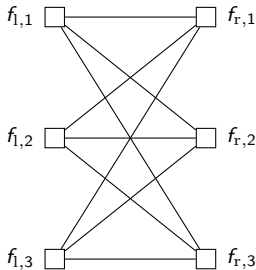
# Graphical-model-based approximation method

5. The **Bethe approximation** of the partition function, *i.e.*, the **Bethe partition function**, is defined to be

$$Z_B(N) \triangleq \exp\left(-\min_{\beta \in \mathcal{L}(N)} F_B(\beta)\right),$$

where  $F_B$  is the **Bethe free energy (BFE)** function,

where  $\mathcal{L}(N)$  is the **local marginal polytope** (LMP) (see, *e.g.*, [Wainwright and Jordan, 2008]).



6. Then we run the **sum-product algorithm (SPA)**,  
a.k.a. **belief propagation (BP)**, on the S-FG  $N$  to get  $Z_B(N)$ .

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# Main results

1. The **projection** of the **LMP** on the **edges** in  $N$  **equals**  $\text{conv}(\mathcal{C})$ .  
(For general S-FGs, this projection is a **relaxation** of  $\text{conv}(\mathcal{C})$ , *i.e.*,  $\text{conv}(\mathcal{C})$  is a **strict subset** of this **projection**.)
2. For the **typical case** where  $N$  has an **SPA fixed point** consisting of **positive-valued messages only**, the SPA finds the value of  $Z_B(N)$  **exponentially fast**.
3. The **BFE function** has some **convexity properties**.

## Comments

- ▶ A **generalization** of parts of the results in [Vontobel, 2013].
- ▶ Even though the S-FG has a **non-trivial cyclic structure**, the SPA has **a good performance**.

# Main results

## Comments

For the setup where  $n = m$ ,  $r_i = 1$ , and  $c_j = 1$ , it holds that

- ▶  $\mathcal{C} = \{\mathbf{x} \mid \mathbf{x} \text{ is a permutation matrix of size } n\text{-by-}n\}$
- ▶ The projection of the LMP on the edges equals the set of doubly stochastic matrices of size  $n\text{-by-}n$ .

## Birkhoff–von Neumann theorem

The set of doubly stochastic matrices of size  $n\text{-by-}n$  is the convex hull of the set of the permutation matrices of size  $n\text{-by-}n$ .

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The main result that  $\text{conv}(\mathcal{C})$  equals the projection of the LMP on the edges for our considered S-FG, can be viewed as a generalization.

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# A more general setup

## An example S-FG

Consider  $n = m = 3$  and  $r_i = c_j = 2$ . Then

$$f_{1,i}(\mathbf{x}(i,:)) = \begin{cases} 1 & \text{if } \mathbf{x}(i,:) \in \{(1, 1, 0), (0, 1, 1), (1, 0, 1)\} \\ 0 & \text{otherwise} \end{cases},$$

which corresponds to a **multi-affine homogeneous real stable (MAHRS) polynomial** w.r.t. the **indeterminates** in  $\mathbf{L} \triangleq (L_1, L_2, L_3) \in \mathbb{C}^3$ :

$$\begin{aligned} p_i(\mathbf{L}) &= \sum_{\mathbf{x}(i,:) \in \{0,1\}^3} f_{1,i}(\mathbf{x}(i,:)) \cdot \prod_{j \in [3]} (L_j)^{x(i,j)} \\ &= L_1 \cdot L_2 + L_2 \cdot L_3 + L_1 \cdot L_3, \end{aligned}$$

## Remark

- For details of **real stable polynomials**, see, e.g., [Gharan, 2020]

Consider a **more general** setup where **each local function** is defined based on a **(possibly different) MAHRS polynomial**.

Do the previous results **hold** in this **more general setup**?

**Yes!**

# An MAHRS Polynomials-based S-FG

The standard factor graph (S-FG)  $\mathcal{N}$  consists of

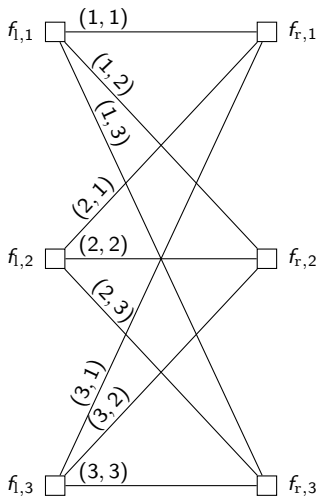
1. **edges:**  $(1, 1), (1, 2), \dots, (3, 3)$ ;

2. **Binary** matrix

$$\mathbf{x} \triangleq \begin{pmatrix} x(1, 1) & x(1, 2) & x(1, 3) \\ x(2, 1) & x(2, 2) & x(2, 3) \\ x(3, 1) & x(3, 2) & x(3, 3) \end{pmatrix}.$$

3. **Nonnegative-valued** local functions

$$f_{l,1}, \dots, f_{r,3};$$



# An MAHRS Polynomials-based S-FG

6. The **local function**  $f_{l,i}$  on the **LHS** is defined to be the mapping:

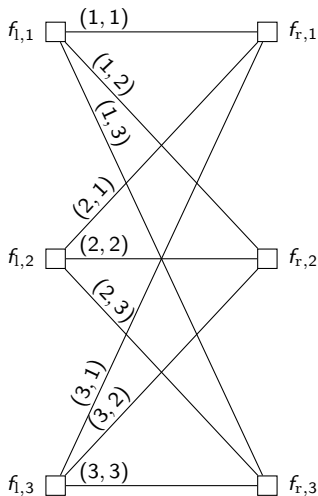
$$\{0, 1\}^3 \rightarrow \mathbb{R}_{\geq 0}, \quad \mathbf{x}(i, :) \mapsto f_{l,i}(\mathbf{x}(i, :))$$

such that it corresponds to an **MAHRS polynomial**.

7. The **support** of  $f_{l,i}$ :

$$\mathcal{X}_{f_{l,i}} \triangleq \{\mathbf{x}(i, :) \in \{0, 1\}^3 \mid f_{l,i}(\mathbf{x}(i, :)) > 0\}.$$

8. A **similar idea** in the definitions of  $f_{r,j}$  and  $\mathcal{X}_{f_{r,j}}$  on the **RHS**.



# An MAHRS Polynomials-based S-FG

9. The **nonnegative-valued global function**:

$$\begin{aligned} g(\mathbf{x}) \triangleq & f_{l,1}(\mathbf{x}(1,:)) \cdot f_{l,2}(\mathbf{x}(2,:)) \\ & \cdot f_{l,3}(\mathbf{x}(3,:)) \cdot f_{r,1}(\mathbf{x}(:,1)) \\ & \cdot f_{r,2}(\mathbf{x}(:,2)) \cdot f_{r,3}(\mathbf{x}(:,3)). \end{aligned}$$

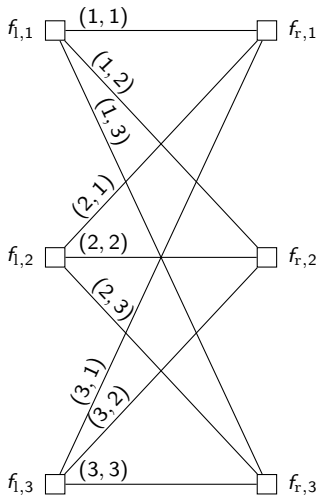
10. The set of **valid configurations**:

$$\mathcal{C} \triangleq \{ \mathbf{x} \in \{0,1\}^{3 \times 3} \mid g(\mathbf{x}) > 0 \},$$

which is also the **support** of the **global function**.

11. The **partition function**:

$$Z(N) \triangleq \sum_{\mathbf{x} \in \mathcal{C}} g(\mathbf{x}).$$





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# Known results

Consider an **S-FG  $N$**  where **each local function** is defined based on a (possibly different) **MAHRS** polynomial.

## Remarks

- ▶ Exactly computing  $Z(N)$  is a **#P-complete problem** in general.
- ▶ **Run the SPA** to find the value of the **Bethe partition function**  $Z_B(N)$  that **approximates**  $Z(N)$ .
- ▶ [Straszak and Vishnoi, 2019, Theorem 3.2]:  $Z_B(N) \leq Z(N)$ .
- ▶ **Other real-stable-polynomial-based approximation of  $Z(N)$**   
[Gurvits, 2015, Brändén et al., 2023].

# Main results

Consider an **S-FG N** where **each local function** is defined based on a (possibly different) **MAHRS** polynomial.

- ▶ The **support**  $\mathcal{X}_{f_{1,i}}$  on the LHS corresponds to **a set of bases of a matroid** [Brändén, 2007].
- ▶ The support of the **product** of the **local functions** on the **LHS** is  $\{\mathcal{X}_{f_{1,1}} \times \mathcal{X}_{f_{1,2}} \times \cdots \times \mathcal{X}_{f_{1,n}}\}$ .
- ▶ Similarly for the local functions and the **support** on the **LHS**.
- ▶ The support of the **global function** equals the **intersection** of the bases of **matroids**:

$$\mathcal{C} = \{\mathcal{X}_{f_{1,1}} \times \mathcal{X}_{f_{1,2}} \times \cdots \times \mathcal{X}_{f_{1,n}}\} \cap \{\mathcal{X}_{f_{r,1}} \times \mathcal{X}_{f_{r,2}} \times \cdots \times \mathcal{X}_{f_{r,m}}\}$$

# Main results

1. The **convex hull**  $\text{conv}(\mathcal{C})$  is the **projection of the LMP** on the **edges**.  
(Based on results on intersection of matroids [Oxley, 2011].)
2. For the typical case where the S-FG has an SPA **fixed point** consisting of **positive-valued messages only**, the SPA finds the value of  $Z_B(N)$  **exponentially fast**.  
(Based on the properties of **real stable polynomials** in [Brändén, 2007].)
3. The **Bethe free energy function**  $F_B$  has some **convexity properties**.  
The proof of the convexity is **new**.  
(Based on the **dual** form of  $Z_B(N)$  in [Straszak and Vishnoi, 2019, Anari and Gharan, 2021].)

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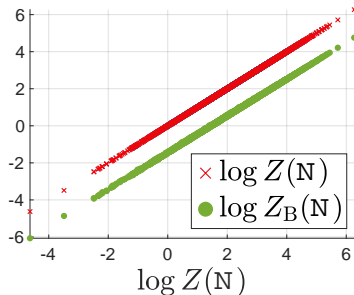
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# Numerical results

## Setup

- ▶ We first consider the case  $n = m = 6$  and  $r_i = c_j = 2$ .
- ▶ We independently randomly generate 3000 instances of  $N$ .



## Observation

- ▶  $Z_B(N) \leq Z(N)$  ([Straszak and Vishnoi, 2019, Theorem 3.2]).
- ▶  $Z_B(N)$  provides a **good estimate** of  $Z(N)$  in this case.

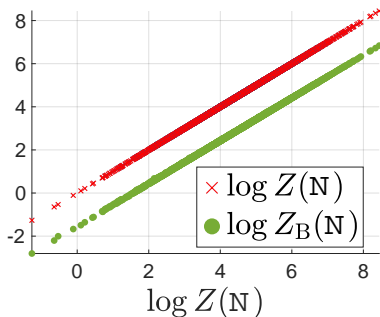
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## Setup

Consider **the same setup** as the previous case, but with  $n = m = 6$  **replaced** by  $n = m = 7$ .

## Observation

We can make **similar observations**.



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## Future work

- ▶ Consider a **more general** S-FG, where each local function corresponds to a **more general** polynomial.
- ▶ Prove the **convergence** of the SPA for a **more general** S-FG.

# Connection to other works

- ▶ **Polynomial approaches** to approximate **partition functions**.  
[Gurvits, 2011, Straszak and Vishnoi, 2017, Anari and Gharan, 2021]
- ▶ The properties of **real stable** polynomials and the **partition functions**.  
[Brändén, 2014, Borcea and Brändén, 2009, Borcea et al., 2009]

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# Thank you!

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