# Gaussian Matching

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# 1 Model Formulation

#### 1.1 Notations

- Let the lowercase letters (e.g., a, c) denote the scalar; the bold lowercase letters (e.g.,  $\omega, v$ ) denote the vector; the uppercase letters (e.g., S, T) denote the index set with elements in  $\mathbb{Z}_+$ ; the bold uppercase letters (e.g., P, Q) denote the dimension-2 index set with elements in the form (i, j) where  $i, j \in \mathbb{Z}_+$ ; and the calligraphy letters (e.g., A, B) denote the tensor of order three or greater.
- For a positive integer n, let [n] denote the index set  $\{1, \ldots, n\}$ .
- For an index set S and a positive integer m, let  $S^m$  denote the dimension-m vector space of S, where  $S^m = \{(i_1, \ldots, i_m) : i_k \in S, \text{ for all } k \in [m]\}.$
- For two index sets S and T, we call the function  $\pi: S \mapsto T$  the perfect matching between S and T when  $\pi(i_1) = \pi(i_2)$  if and only if  $i_1 = i_2$  for any  $i_1, i_2 \in S$ . When T = S, we call the  $\pi$  the permutation on S.
- For a perfect matching  $\pi: S \mapsto T$ , we call the dimension-2 index set  $\mathbf{P} = \{(i, \pi(i)) : i \in S\}$  the set corresponding to  $\pi$ , and we call  $\pi$  the perfect matching corresponding to  $\mathbf{P}$ .
- For a perfect matching  $\pi: S \mapsto T$  and an index set  $S_0 \subset S$ , let  $\pi|_{S_0}: S_0 \mapsto T_0$  denote the sub-matching of  $\pi$  for the nodes in  $S_0$ , where  $T_0 = \{\pi(i) : i \in S_0\} \subset T$ .
- For a perfect matching  $\pi: S \mapsto T$  and a dimension-m vector  $\mathbf{v} = (v_1, \dots, v_m) \in S^m$ , let  $\pi \circ \mathbf{v} = (\pi(v_1), \dots, \pi(v_m)) \in T^m$  denote the permutation of the vector  $\mathbf{v}$ .
- Let  $\mathcal{A} \in \mathbb{R}^{n^{\otimes m}}$  denote an order-m real tensor of dimension n on each mode. For the vector  $\boldsymbol{\omega} = (\omega_1, \dots, \omega_m) \in [n]^m$ , we use  $\mathcal{A}_{\boldsymbol{\omega}}$  to denote the  $(\omega_1, \dots, \omega_m)$ -th entry of  $\mathcal{A}$ .
- We call a tensor  $\mathcal{A} \in \mathbb{R}^{n^{\otimes m}}$  super-symmetric if for all  $\boldsymbol{\omega} = (\omega_1, \dots, \omega_m) \in [n]^m$  we have  $\mathcal{A}_{\boldsymbol{\omega}} = \mathcal{A}_{\pi \circ \boldsymbol{\omega}}$  for all permutations  $\pi$  on the set  $\{\omega_1, \dots, \omega_m\}$ .
- Let  $\times_k$  denote the tensor-by-matrix multiplication on the k-th mode.
- Let  $\|\cdot\|_F$  denote the Frobenius norm for tensors. Let  $\langle\cdot,\cdot\rangle$  denote the inner product for tensors.

## 1.2 Higher-order Correlated Winger Model

Consider two random super-symmetric tensors  $\mathcal{A}, \mathcal{B}' \in \mathbb{R}^{n^{\otimes m}}$ . Assume that all the pairs  $\{(\mathcal{A}_{\omega}, \mathcal{B}'_{\omega}) : \omega \in [n]^m \cap \{\omega : \omega_1 \leq \cdots \leq \omega_m\}\}$  follow the i.i.d. correlated multivariate zero-mean Gaussian distribution with variance 1 and correlation  $\rho \in (0, 1)$ ; i.e.,

$$\begin{pmatrix} \mathcal{A}_{\boldsymbol{\omega}} \\ \mathcal{B}'_{\boldsymbol{\omega}} \end{pmatrix} \sim \mathcal{N} \left( \boldsymbol{0}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right), \quad \text{and} \quad \begin{pmatrix} \mathcal{A}_{\boldsymbol{\omega}} \\ \mathcal{B}'_{\boldsymbol{\omega}} \end{pmatrix} \text{ is independent with } \begin{pmatrix} \mathcal{A}_{\boldsymbol{\omega}'} \\ \mathcal{B}'_{\boldsymbol{\omega}'} \end{pmatrix},$$

for all  $\omega' \neq \omega$  and  $\omega' \in [n]^m \cap \{\omega : \omega_1 \leq \cdots \leq \omega_m\}$ . The tensors  $\mathcal{A}, \mathcal{B}'$  are two correlated Winger tensors. Let  $\pi^*$  be a permutation on [n], and  $\Pi^* \in \{0,1\}^{n \times n}$  denote the corresponding permutation matrix with entries  $\Pi_{ij}^* = 1$  if  $j = \pi^*(i)$  and  $\Pi_{ij}^* = 0$ , otherwise. Consider the permuted tensor  $\mathcal{B}$  such that for all  $\omega \in [n]^m$ 

$$\mathcal{B}_{\omega} = \mathcal{B}'_{\pi^* \circ \omega}$$
, or equivalently  $\mathcal{B} = \mathcal{B}' \times_1 \Pi^* \times_2 \cdots \times_m \Pi^*$ .

We call the pair  $(i,k) \in [n]^2$  as a true pair if  $k = \pi^*(i)$ , and (i,k) is a fake pair, otherwise.

Our goal is to recover  $\pi^*$  (or equivalently  $\Pi^*$ ) observing  $\mathcal{A}, \mathcal{B}$ .

#### 1.3 Maximum Likelihood Estimate

Let  $\Sigma$  denote the covariance matrix  $\begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$  with inverse  $\Sigma^{-1} = \frac{1}{1-\rho^2} \begin{pmatrix} 1 & -\rho \\ -\rho & 1 \end{pmatrix}$ . The permutation  $\pi^*$  (or equivalently permutation matrix  $\Pi$ ) and the correlation  $\rho$  are unknown parameters, and  $\pi^*$  is our of main interest. We have the likelihood for the higher-order correlated Winger model

$$\mathcal{L}(\Pi, \rho | \mathcal{A}, \mathcal{B}) = \frac{1}{[2\pi \det(\Sigma)]^{n^m/2}} \exp\left(-\frac{1}{2} \sum_{\boldsymbol{\omega} \in [n]^m} (\mathcal{A}_{\pi \circ \boldsymbol{\omega}}, \mathcal{B}_{\boldsymbol{\omega}}) \Sigma^{-1} (\mathcal{A}_{\pi \circ \boldsymbol{\omega}}, \mathcal{B}_{\boldsymbol{\omega}})^T\right)$$

$$= \frac{1}{[2\pi \det(\Sigma)]^{n^m/2}} \exp\left(-\frac{1}{2(1-\rho^2)} \left[\|\mathcal{A}\|_F^2 + \|\mathcal{B}\|_F^2 - 2\rho \left\langle \mathcal{A} \times_1 \Pi \times_2 \dots \times_m \Pi, \mathcal{B} \right\rangle \right]\right).$$

For any  $\rho \in (0,1)$ , consider the estimator

$$\hat{\Pi}(\rho) = \underset{\Pi}{\arg \max} \, \mathcal{L}(\Pi | \rho, \mathcal{A}, \mathcal{B}) = \underset{\Pi}{\arg \max} \, \langle \mathcal{A} \times_1 \, \Pi \times_2 \cdots \times_m \, \Pi, \mathcal{B} \rangle \,.$$

Note that  $\hat{\Pi}(\rho)$  is independent with  $\rho$ . Therefore, we let  $\hat{\Pi}$  denote the estimator  $\hat{\Pi}(\rho)$ , and  $\hat{\Pi}$  is the MLE of  $\Pi^*$ . The permutation  $\hat{\pi}$  corresponding to  $\hat{\Pi}$  is the MLE of  $\pi^*$ .

# 2 Algorithm

# 2.1 Matching via Empirical Distributions

We describe each node by the slice empirical distribution and adapt the sup-norm distance for distributions as the similarity measure to construct the mapping. Specifically, we define the sup-norm distance for all pairs  $(i, k) \in [n]^2$  as

$$d_{ik} = \sup_{t \in \mathbb{R}} |F_n^i(t) - G_n^k(t)|, \tag{1}$$

where for all  $t \in \mathbb{R}$ 

$$F_n^i(t) = \frac{1}{n^{m-1}} \sum_{\omega \in [n]^{m-1}} \mathbb{1} \{ \mathcal{A}_{i,\omega} \le t \}, \quad G_n^k(t) = \frac{1}{n^{m-1}} \sum_{\omega \in [n]^{m-1}} \mathbb{1} \{ \mathcal{B}_{k,\omega} \le t \}$$

are slice empirical distributions for node i with observation  $\mathcal{A}$  and node k with observation  $\mathcal{B}$ , respectively. The sup-norm distance  $d_{ik}$  is smaller when  $F_n^i$  are  $G_n^k$  are more correlated, which motivates our Algorithm 1 for Gaussian tensor matching.

#### Algorithm 1 Gaussian tensor matching via empirical distribution

Input: Gaussian tensors  $\mathcal{A}, \mathcal{B} \in \mathbb{R}^{n^{\otimes m}}$ 

- 1: Calculate the sup-norm distances  $d_{ik}$  as (1) for all pairs  $(i,k) \in [n]^2$ .
- 2: Obtain the set  $P = \{(i, k) \in [n]^2 : d_{ik} \text{ is no larger than the } n\text{-th smallest } d_{ik}\}.$
- 3: if there exists a permutation on [n],  $\hat{\pi}$ , corresponding to the set **P** then
- 4: Output  $\hat{\pi}$ .
- 5: **else**
- 6: Output error.
- 7: end if

**Output:** Estimated permutation  $\hat{\pi}$  or error.

Following theorem shows the guarantee for Algorithm 1 to exactly recover true permutation  $\pi^*$ .

**Theorem 2.1** (Guarantee for Algorithm 1). Let  $\sigma^2 = \sqrt{1-\rho^2}$ . Suppose  $\sigma \leq c \log^{-1} n$  for some sufficiently small positive constant c. Algorithm 1 exactly recovers the true permutation  $\pi^*$  with probability tends to 1 as  $n \to \infty$ .

## 2.2 Improved Matching with Seeded Algorithm

We improve the Algorithm 1 with seeded algorithm. Our seeded algorithm involves three steps: (1) generating seeds that reveals the true permutation  $\pi^*$  for a subset of nodes; (2) recovering the full permutation with the seed; (3) refining the estimated permutation in (2) to achieve exact recovery.

Specifically, we consider the seed that involves high-similarity and high-degree pairs in step (1). We measure the similarity by the sup-norm distance defined in (1). The "degree" of node i in  $\mathcal{A}$  and node k in  $\mathcal{B}$  for all  $i, k \in [n]$  are represented as

$$a_i = \frac{1}{n^{(m-1)/2}} \sum_{\boldsymbol{\omega} \in [n]^{m-1}} \mathcal{A}_{i,\boldsymbol{\omega}}, \quad \text{and} \quad b_k = \frac{1}{n^{(m-1)/2}} \sum_{\boldsymbol{\omega} \in [n]^{m-1}} \mathcal{B}_{k,\boldsymbol{\omega}}.$$
 (2)

Hence, we consider the following seed set Q with given thresholds  $\xi, \zeta$ 

$$Q = \{(i,k) \in [n]^2 : a_i, b_k \ge \xi, d_{ik} \le \zeta\}.$$
(3)

The Q contains more seeds with a smaller  $\xi$  and larger  $\zeta$ . As our proof shows later, the set Q with proper thresholds  $\xi$  and  $\zeta$  contains only true pairs with high probability. Suppose that there exists a perfect matching  $\pi_0: S \mapsto T$  corresponding to Q, where S and T are two subsets of [n]. Then, we solve the rest permutations by transferring the multiway tensor matching to a bipartite matching problem with  $\pi_0$ . Detail procedures are in Algorithm 2.

Following theorem shows the guarantee for Algorithm 2 to exactly recover true permutation  $\pi^*$ .

## Algorithm 2 Improved Gaussian tensor matching with seeded algorithm

#### Step 1: Seeds generation

**Input:** Gaussian tensors  $\mathcal{A}, \mathcal{B} \in \mathbb{R}^{n^{\otimes m}}$ , thresholds  $\xi$  and  $\zeta$ .

- 1: Calculate the sup-norm distances  $d_{ik}$  as (1) for all pairs  $(i,k) \in [n]^2$  and the degrees  $a_i$  and  $b_i$  as (2) for all  $i \in [n]$ .
- 2: Obtain the seed set Q as (3) with  $\xi$  and  $\zeta$ .
- 3: if there exists a perfect matching  $\pi_0: S \mapsto T$  corresponding to Q then
- 4: Output  $\pi_0$ .
- 5: **else**
- 6: Stop the entire Algorithm 2 immediately and output error.
- 7: end if

**Output:** Perfect matching  $\pi_0$  or error.

#### Step 2: Seeded matching

**Input:** Gaussian tensors  $\mathcal{A}, \mathcal{B} \in \mathbb{R}^{n^{\otimes m}}$  and the perfect matching  $\pi_0 : S \mapsto T$  from **Step 1**.

8: Calculate the analogy of sample covariance  $H_{ik}$  for all pairs (i, k) such that  $i \in S^c$  and  $k \in T^c$ , where  $S^c = [n]/S, T^c = [n]/T$ , and

$$H_{ik} = \sum_{\boldsymbol{\omega} \in S^{m-1}} \mathcal{A}_{i,\boldsymbol{\omega}} \mathcal{B}_{k,\pi_0 \circ \boldsymbol{\omega}}.$$

9: Find the optimal perfect matching  $\tilde{\pi}_1 \colon S^c \mapsto T^c$  such that

$$\tilde{\pi}_1 = \underset{\pi \colon S^c \mapsto T^c}{\arg \max} \sum_{i \in S^c} H_{i\pi(i)}.$$

10: Concatenate the matching  $\pi_0$  and  $\tilde{\pi}_1$  to a permutation  $\pi_1$  on [n] such that  $\pi_1|_S = \pi_0$  and  $\pi_1|_{S^c} = \tilde{\pi}_1$ .

Output: Estimated permutation  $\pi_1$ .

#### Step 3: Non-iterative clean-up

**Input:** Gaussian tensors  $\mathcal{A}, \mathcal{B} \in \mathbb{R}^{n^{\otimes m}}$  and the permutation  $\pi_1$  on [n] from **Step 2**.

- 11: Calculate  $W_{ik} = \sum_{\boldsymbol{\omega} \in [n]^{m-1}} \mathcal{A}_{i,\boldsymbol{\omega}} \mathcal{B}_{k,\pi_1 \circ \boldsymbol{\omega}}$  for all pairs  $(i,k) \in [n]^2$ .
- 12: Obtain the set  $P = \{(i, k) \in [n]^2 : W_{ik} \text{ is no smaller than the } n\text{-th largest } W_{ik}\}.$
- 13: if there exists a permutation on [n],  $\hat{\pi}$ , corresponding to the set **P** then
- 14: Output  $\hat{\pi}$ .
- 15: **else**
- 16: Output error.
- 17: end if

**Output:** Estimated permutation  $\hat{\pi}$  or error.

**Theorem 2.2** (Guarantee for Algorithm 2). Let  $\sigma^2 = \sqrt{1-\rho^2}$ . Suppose  $\sigma \leq c \log^{-1/3(m-1)} n$  for some sufficiently small positive constant c. Choose thresholds  $\xi \geq c_1 \sqrt{\log^{1/(m-1)} n}$  and  $\zeta \leq c_2 \sqrt{\sigma/n^{m-1}}$  for some positive constants  $c_1, c_2$ . Algorithm 2 exactly recovers the true permutation  $\pi^*$  with probability tends to 1 as  $n \to \infty$ .

# References