

# Iteration Step in hDCBM

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## 1 Algorithm

**Changes in initialization:**

1. Change the constrain  $\frac{1}{p_a} \sum_{j:z_j=a} \theta_j^2 \approx 1$  to  $\frac{1}{p_a} \sum_{j:z_j=a} \theta_j \approx 1$ ;
2. Change the weighted  $k$ -means clustering to weighted  $k$ -median clustering.

These changes may benefit the estimation of  $\mathcal{S}$  without estimating  $\theta_j$ , and  $k$ -median won't affect the clustering too much (based on previous conclusion,  $k$ -median has extra  $\sqrt{p}$  term compared with  $k$ -means).

**Possible Algorithm**

See Algorithm 1.

## 2 Convergence of Iteration

**Lemma 1** (Conjecture). *Suppose  $\delta = o(1)$  and  $\max_{j \in [p]} \theta_j = o(p/r)$ . We have the same result as Theorem 3 in Han et al. (2020).*

**Remark 1.** The reason why we do not use the proof in Gao et al. (2018) is that they have an “assortative” assumption, which implies the in-community connection is stronger than between-community connection. We do not impose such assumption in our case. Also, previous precision matrix clustering also uses the proof idea of Han et al. (2020).

**Proof Sketch**

Similar with Han et al. (2020), we would like to decompose the misclassification error as

$$\ell^{(t+1)} = \xi + \ell^{(t)},$$

where  $\xi$  is the oracle error given true membership. The difficulties in the proof include:

1. Find the exponential upper bound of  $\xi$ . In precision matrix case, we found the estimation error of  $\hat{\theta}_{MLE}$ . However, Algorithm 1 may not output MLE even with given true  $z^*$ , and we avoid the estimation of  $\theta$  by normalization. So, the error of oracle error is a kind of new problem. Also, binary data may be a difficulty.
2. Need to check whether the error decomposition is valid. Again, in precision matrix, we have the estimation error of  $\hat{\theta}_{MLE}$  and the decomposition rely on the property of MLE. Here we need to check the decomposition without the estimation of  $\theta$ .

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**Algorithm 1** High-order degree-corrected Lloyd Algorithm (HDCLloyd)

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**Input:** Observation  $\mathcal{Y} \in \mathbb{R}^{p \times p \times p}$ , initialization  $\{z^{(0)} \in [r]^p\}$ , iteration number  $T$ , SCORE normalization function  $h$

- 1: **for**  $t = 0$  to  $T - 1$  **do**
- 2:     Update the block means

$$\mathcal{S}_{abc}^{(t)} = \text{Average} \left\{ \mathcal{Y}_{i,j,k} : z_i^{(t)} = a, z_j^{(t)} = b, z_k^{(t)} = c \right\}$$

- 3:     **for**  $k \in [3]$  **do**
- 4:         **for**  $j \in [p]$  **do**
- 5:             (Take  $k = 1$  as an example) Calculate  $\mathcal{Y}_1^{(t)} \in \mathbb{R}^{p \times r \times r}$  such that

$$\mathcal{Y}_{1,j,i_1,i_2}^{(t)} = \text{Average} \left\{ \mathcal{Y}_{j,j_1,j_2} : z_{j_1}^{(t)} = i_1, z_{j_2}^{(t)} = i_2 \right\}.$$

- 6:             Calculate the normalized metrication  $\mathbf{Y}_1^{(t)} = \mathcal{M}_1(\mathcal{Y}_1^{(t)})$  and the  $\mathbf{S}_1^{(t)} = \mathcal{M}_1(\mathcal{S}_1)$  as

$$\mathbf{Y}_{1j}^{s,(t)} = \frac{\mathbf{Y}_{1j}^{(t)}}{h(\mathbf{Y}_{1j}^{(t)})}, \quad \mathbf{S}_{1a}^{s,(t)} = \frac{\mathbf{S}_{1a}^{(t)}}{h(\mathbf{S}_{1a}^{(t)})}, \quad j \in [p], a \in [r].$$

- 7:             Update the membership

$$z_j^{(t+1)} = \arg \min_{a \in [r]} h(\mathbf{Y}_{1j}^{(t)}) \left\| \mathbf{Y}_{1j}^{s,(t)} - \mathbf{S}_{1a}^{s,(t)} \right\|.$$

- 8:             **end for**
  - 9:         **end for**
  - 10: **end for**
  - Output:**  $\{z^{(T)} \in [r]^p\}$
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## References

- Gao, C., Ma, Z., Zhang, A. Y., and Zhou, H. H. (2018). Community detection in degree-corrected block models. *The Annals of Statistics*, 46(5):2153–2185.
- Han, R., Luo, Y., Wang, M., and Zhang, A. R. (2020). Exact clustering in tensor block model: Statistical optimality and computational limit. *arXiv preprint arXiv:2012.09996*.