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An iterative clustering algorithm for the Contextual Stochastic Block Model with optimality guarantees

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Abstract

Real-world networks often come with side information that can help to improve the performance of network analysis tasks such as clustering. Despite a large number of empirical and theoretical studies conducted on network clustering methods during the past decade, the added value of side information and the methods used to incorporate it optimally in clustering algorithms are relatively less understood. We propose a new iterative algorithm to cluster networks with side information for nodes (in the form of covariates) and show that our algorithm is optimal under the Contextual Symmetric Stochastic Block Model. Our algorithm can be applied to general Contextual Stochastic Block Models and avoids hyperparameter tuning in contrast to previously proposed methods. We confirm our theoretical results on synthetic data experiments where our algorithm significantly outperforms other methods, and show that it can also be applied to signed graphs. Finally we demonstrate the practical interest of our method on real data.

1 Introduction

The Stochastic Block Model (SBM) is a popular generative model for random graphs – introduced by Holland et al. (1983) – which captures the community structures of networks often observed in the real world. Here, edges are independent Bernoulli random variables with the probability of connection between two nodes depending only on the communities to which they belong. It is typically used as a benchmark to measure the performance of clustering algorithms. However, real-world networks often come with side information in the form of nodes covariates which can often be used to improve clustering performance. The Contextual Stochastic Block Model (CSBM) is a simple extension of the SBM that incorporates such side information: each node is associated with a Gaussian vector of parameters depending only on the community to which the node belongs; see Section 2 for details.

Several variants of this model and clustering algorithms have been proposed in the literature. These methods include model-based approaches (Mele et al., 2019; Weng and Feng, 2016), spectral methods (Binkiewicz et al., 2017), modularity based optimization methods (Zhang et al., 2015) and semidefinite programming (SDP) based approaches (Yan and Sarkar, 2020). Even if some of these algorithms come with some theoretical guarantees, the added value of side information is not well understood. The recent works of Abbe et al. (2020), Lu and Sen (2020) and Ma and Nandy (2021) clarify the situation by establishing information theoretic thresholds for exact recovery and detection in a particular case. However, the algorithm presented in the former work is not likely to be extended to a general CSBM with more than two (possibly unequal-sized) communities, while the latter two results focus on detection rather than consistency.

Our contributions. We make the following contributions in this paper.

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- We propose a new iterative algorithm for clustering networks that is fast and is applicable to various settings including the general CSBM and also signed weighted graphs as shown in experiments.
- The proposed algorithm is analyzed under the Contextual Symmetric SBM (CSSBM) and we show that its rate of convergence is statistically optimal. As a byproduct, we derive the threshold for exact recovery with K communities under the CSSBM, thus extending the recent result of Abbe et al. (2020) which was obtained in a slightly different setting for $K = 2$.
- We confirm the theoretical properties of our algorithm through experiments on simulated data showing that our method outperforms existing algorithms, not only under the CSBM but also under the Signed SBM the latter of which models community structure in signed networks (Cucuringu et al., 2019). Finally, we provided a real data application of our algorithm.

Related work. Our iterative method can be thought of as a Classification-EM algorithm (Celeux and Govaert, 1992), hereafter referred to as C-EM, where instead of using the likelihood we used a least squares criterion. Such ideas were first applied and analyzed under various models including associative SBM by Lu and Zhou (2016) and then extended to a general method by Gao and Zhang (2019). Recently, such ideas were also successfully applied to the Gaussian Tensor Block Model (Han et al., 2020) and a general Gaussian Mixture Model (GMM) (Chen and Zhang, 2021). However, the previously obtained results can not be directly applied to our framework and several adaptations are required due to dependencies arising in the SBM, along with the heterogeneity of the data. Iterative refinement algorithms can also be derived naturally from the Power Method (Wang et al., 2021; Ndaoud et al., 2019) or alternative optimization methods (Chi et al., 2019).

Notation. We use lowercase letters (ϵ, a, b, \dots) to denote scalars and vectors, except for universal constants that will be denoted by c_1, c_2, \dots for lower bounds, and C_1, C_2, \dots for upper bounds and some random variables. We will sometimes use the notation $a_n \lesssim b_n$ (or $a_n \gtrsim b_n$) for sequences $(a_n)_{n \geq 1}$ and $(b_n)_{n \geq 1}$ if there is a constant $C > 0$ such that $a_n \leq Cb_n$ (resp. $a_n \geq Cb_n$) for all n . If $a_n \lesssim b_n$ and $a_n \gtrsim b_n$, then we write $a_n \asymp b_n$. Matrices will be denoted by uppercase letters. The i -th row of a matrix A will be denoted as $A_{i \cdot}$ and depending on the context can be interpreted as a column vector. The column j of A will be denoted by $A_{\cdot j}$, and the (i, j) th entry by A_{ij} . The transpose of A is denoted by A^\top and $A_{\cdot j}^\top$ corresponds to the j th row of A^\top by convention. I_k denotes the $k \times k$ identity matrix. For matrices, we use $\|\cdot\|$ and $\|\cdot\|_F$ to respectively denote the spectral norm (or Euclidean norm in case of vectors) and Frobenius norm. The number of non zero entries of a matrix A is denoted $nnz(A)$.

2 The statistical framework

The CSBM consists of a graph encoded in an adjacency matrix $A \in \{0, 1\}^{n \times n}$ and nodes covariates forming a matrix $X = [X_1 \ X_2 \ \dots \ X_n]^\top \in \mathbb{R}^{n \times d}$ where d is the dimension of the covariate space. The graph and the covariates are generated as follows.

The graph part of the data is generated from a Stochastic Block Model (SBM) which is defined by the following parameters.

- The set of nodes $\mathcal{N} = [n]$.
- Communities $\mathcal{C}_1, \dots, \mathcal{C}_K$, of respective sizes n_1, \dots, n_K , forming a partition of \mathcal{N} .
- A membership matrix $Z \in \mathcal{M}_{n, K}$ where $\mathcal{M}_{n, K}$ denotes the class of membership matrices. Here, $Z_{ik} = 1$ if node i belongs to \mathcal{C}_k , and is 0 otherwise. Each membership matrix Z can be associated bijectively with a function $z : [n] \rightarrow [K]$ such that $z(i) = z_i = k$ where k is the unique column index satisfying $Z_{ik} = 1$. To each matrix $Z \in \mathcal{M}_{n, K}$ we can associate a matrix W by normalizing the columns of Z in the ℓ_1 norm: $W = ZD^{-1}$ where $D = \text{diag}(n_1, \dots, n_K)$. This implies that $W^\top Z = I_K = Z^\top W$.
- A symmetric, connectivity matrix of probabilities between communities

$$\Pi = (\pi_{kk'})_{k, k' \in [K]} \in [0, 1]^{K \times K}.$$

We additionally assume that the communities are approximately well balanced, i.e.,

$$\frac{n}{\alpha K} \leq n_k \leq \frac{\alpha n}{K} \quad \forall k \in [K],$$

for some constant $\alpha > 1$. Denoting $P = (p_{ij})_{i,j \in [n]} := Z\Pi Z^T$, a graph \mathcal{G} is distributed according to SBM(Z, Π) if the entries of the corresponding symmetric adjacency matrix A are generated by

$$A_{ij} \stackrel{\text{ind.}}{\sim} \mathcal{B}(p_{ij}), \quad 1 \leq i \leq j \leq n,$$

where $\mathcal{B}(p)$ denotes a Bernoulli distribution with parameter p . Hence the probability that two nodes are connected depends only on their community memberships. We will frequently use the notation E for the centered noise matrix defined as $E_{ij} = A_{ij} - p_{ij}$, and denote the maximum entry of P by $p_{max} = \max_{i,j} p_{ij}$. The latter can be interpreted as the sparsity level of the graph. We will assume throughout that $p_{max} \asymp \log n/n$. If the graph is denser, we are in the exact recovery regime and the problem is easy. If we are in a sparser regime, we would need to regularize the adjacency matrix to enforce concentration, but we prefer to avoid this additional technical difficulty.

For the analysis, we will also consider a special case of the SBM where the communities are equal sized, i.e., $n_k = n/K$ for all $k \in [K]$, and the connectivity matrix is given by

$$\Pi = \begin{pmatrix} p & q & \dots & q \\ q & p & \dots & q \\ \vdots & \vdots & \ddots & \vdots \\ q & q & \dots & p \end{pmatrix} \in [0, 1]^{K \times K}.$$

We will further assume that $p = p' \frac{\log n}{n}$ and $q = q' \frac{\log n}{n}$ for constants p', q' such that $p' > q'$. This model will be referred to as the Symmetric SBM and denoted by SSBM(p, q, n, K).

The **nodes covariates** are generated by a Gaussian Mixture Model (GMM), independent of A conditionally on the partition Z . More formally, for each i ,

$$X_i = \mu_{z_i} + \epsilon_i, \text{ where } \epsilon_i \stackrel{\text{ind.}}{\sim} \mathcal{N}(0, \sigma^2 I_d)$$

with $\mu_k \in \mathbb{R}^d$ for all $k \leq K$ and $\sigma > 0$. We assume that $d = O(n)$. For the ease of exposition we further assume that σ is known but our method can be extended to anisotropic GMM with unknown variance as in Chen and Zhang (2021).

The **misclustering rate** associated to an estimated partition \hat{z} quantifies the number of nodes assigned to a wrong cluster and is formally defined by

$$r(\hat{z}, z) = \frac{1}{n} \min_{\pi \in \mathfrak{S}} \sum_{i \in [n]} \mathbf{1}_{\{\hat{z}(i) \neq \pi(z(i))\}},$$

where \mathfrak{S} denotes the set of permutations on $[K]$. We say that we are in the exact recovery regime if $r(\hat{Z}, Z) = 0$ with probability $1 - o(1)$ as n tends to infinity. If $\mathbb{P}(r(\hat{Z}, Z) = o(1)) = 1 - o(1)$ as n tends to infinity then we are in the weak consistency regime. A more complete overview of the different types of consistency and the sparsity regimes where they occur can be found in Abbe (2018).

3 How to integrate heterogeneous sources of information?

The use of side information should intuitively help to recover clusters that are not well separated on each individual source of information. However, it is not well understood how to integrate two heterogeneous sources of information in the clustering process. Previous attempts (Binkiewicz et al., 2017; Yan and Sarkar, 2020) proceed by directly aggregating the adjacency matrix and a Gram matrix (or Kernel matrix) formed by the covariates, but a lot of information can be lost in the aggregation process. Moreover it is not clear what is the best linear combination of the two matrices. Here we propose a different approach based on a two step algorithm (see Algorithm 1) that fully exploits all information. In the first step we obtain a rough

estimate of the model parameters from the previous estimate of the partition; the initialization methods that can be used are discussed in Section 3.2. Then, in the second step, we iteratively refine the partition, as further explained in Section 3.1. In Section 5.1 we illustrate via experiments that Algorithm 1 outperforms existing methods for cluster recovery in the setting where the clusters are insufficiently separated on a single source of information.

Algorithm 1 Iterative Refinement with Least Squares

Input: $A \in \mathbb{R}^{n \times n}$, $X \in \mathbb{R}^{n \times d}$, $K \in \mathbb{N}^*$, $\sigma > 0$, $Z^{(0)} \in \{0, 1\}^{n \times K}$ a membership matrix and $T \geq 1$.

- 1: **for** $0 \leq t \leq T - 1$ **do**
- 2: Given $Z^{(t)}$, estimate the model parameters: $n_k^{(t)} = |\mathcal{C}_k^{(t)}|$, $W^{(t)} = Z^{(t)}(D^{(t)})^{-1}$ where $D^{(t)} = \text{diag}(n_k^{(t)})_{k \in [K]}$, $\Pi^{(t)} = W^{(t)\top} A W^{(t)}$, and $\mu_k^{(t)} = W_{k:}^{(t)\top} X$, for all $k \leq K$.
- 3: Refine the partition by solving for each $i \in [n]$

$$z_i^{(t+1)} = \arg \min_k \|(A_{i:} W^{(t)} - \Pi_{k:}^{(t)}) \sqrt{\Sigma_k^{(t)}}\|^2 + \frac{\|X_i - \mu_k^{(t)}\|^2}{\sigma^2}$$

where

$$\Sigma_k^{(t)} = \begin{cases} \text{diag}\left(\frac{n_{k'}}{\Pi_{kk'}^{(t)}}\right)_{k' \in [K]} & \text{(IR-LS)} \\ \frac{\min_{k'} n_{k'}^{(t)}}{\max_{k', k''} \Pi_{k'k''}^{(t)}} I_K & \text{(sIR-LS)} \\ \frac{n}{K(p^{(t)} - q^{(t)})} \log\left(\frac{p^{(t)}(1 - q^{(t)})}{q^{(t)}(1 - p^{(t)})}\right) I_K & \text{(IR-LSS)} \end{cases}$$

with $p^{(t)} = K^{-1} \sum_{k \in [K]} \Pi_{kk}^{(t)}$ and $q^{(t)} = (K^2 - K)^{-1} \sum_{k \neq k' \in [K]} \Pi_{kk'}^{(t)}$.

- 4: Form the matrices $Z^{(t+1)}$ from $z^{(t+1)}$.

5: **end for**

Output: A partition of the nodes $Z^{(T)}$.

3.1 The refinement mechanism

At each step t , Algorithm 1 estimates the model parameters given a current estimate of the partition ($W^{(t)}$), then updates the partition by reassigning each node to its closest community. Here, the proximity of a node i to a community k is measured by the distance between its estimated (graph) connectivity profile ($A_{i:} W^{(t)}$) and its covariates (X_i) to the current estimate of the community parameters ($\Pi_{k:}^{(t)}, \mu_k^{(t)}$). Instead of using the Maximum A Priori (MAP) estimator as in C-EM algorithms, we use a least-square criterion. In a model-based perspective, this can be interpreted as a Gaussian approximation of the SBM. We will see later in the experiments that this doesn't lead to a loss of accuracy, and is also faster.

Different variants of our algorithm are possible depending on the way the variance of each community is estimated and integrated in the criterion used for the partition refinement. The general method will be referred as IR-LS, the simplified spherical version is denoted by sIR-LS and the version of the algorithm used for CSSBM is denoted by IR-LSS.

Computational cost. In each iteration, the complexity of estimating the parameters is $O(nnz(A) + nd)$ while that of estimating the partition is $O(nK(K + d))$. So the total cost of IR-LS is $O(T(nnz(A) + nK(\max(K, d))))$. In our setting A is sparse, hence $nnz(A) \asymp n \log n$.

Remark 1. *Algorithm 1 can also be used for clustering weighted signed graphs, as shown later in the experiments. Moreover, it is interesting to note that when there are no covariates, the algorithm can be applied to graphs generated from a general SBM. This is in contrast to the iterative algorithm proposed by Lu and Zhou (2016) that can only be applied to assortative SBMs (see appendix).*

3.2 Initialization

Different strategies can be adopted for initialization. If we assume that the communities are separated on each source of information and that the signal-to-noise ratio (SNR) is large enough to recover a sufficient proportion in each cluster, we can use a spectral method on one source of information (the graph for example). However, it is in general better to combine both sources of information. While one could use the methods proposed in Yan and Sarkar (2020) or Binkiewicz et al. (2017) that also come with some theoretical guarantees, we instead use Algorithm 2 to initialize the partition. This algorithm will be referred to as **EM-Emb**. In our experiments, we used the package `clusterR` (Mouselimis, 2021) for estimating the Gaussian mixture with an EM algorithm. This algorithm is fast, provides a sufficiently accurate estimate of the partition, and avoids hyperparameter tuning.

Algorithm 2 EM on graph embedding and covariates (**EM-Emb**)

Input: The number of communities K , the adjacency matrix A , covariates X .

- 1: Compute $U_K \in \mathbb{R}^{n \times K}$ the matrix formed by the eigenvectors associated with the top- K eigenvalues (in absolute order) of A .
- 2: Merge the columns of U_K with the columns of X to obtain a matrix X' .
- 3: Cluster the rows of X' by using an EM algorithm for GMM.

Output: A partition of the nodes $Z^{(0)}$.

4 Theoretical analysis

In this section, we analyze the variants **sIR-LS** and **IR-LSS** of Algorithm 1. While it is possible to extend the analysis to **IR-LS**, it would be considerably more technical and tedious due to its non-spherical structure. Hence, we will assume here that the covariance matrix $\Sigma_k^{(t)}$ in Algorithm 1 has the form $\lambda^{(t)} I_k$ where $\lambda^{(t)}$ is an appropriate scalar depending on whether we use **sIR-LS** or **IR-LSS**.

In Section 4.1 we will present the general principle for the analysis. Then we will specialize it for analyzing **IR-LSS** (under the CSSBM) in Section 4.2, and prove that the convergence rate obtained is optimal in Section 4.3. Finally we show that the same framework can be used to bound the convergence rate of **sIR-LS** (under the CSBM) in Section 4.4. The details of the proofs are outlined in the appendix.

4.1 Analysis principle

Our analysis is motivated by the general framework recently developed by Gao and Zhang (2019), and also borrows some decomposition techniques used for analyzing Gaussian tensors from Han et al. (2020). However, these results are not directly applicable to our setting due to dependencies arising from symmetry in the SBM. Moreover, we need a tighter control of the error terms than provided by these works.

We will assume w.l.o.g. that $\sigma = 1$ (since σ is assumed to be known in our framework) and that the permutation π that minimizes the distance between $z^{(0)}$ and z is the identity (if not, then replace z by $\pi^{-1}(z)$). Hence there is no label switching ambiguity in the community labels of $z^{(t)}$ because they are determined from $z^{(0)}$.

The first step is to analyze the event “after one refinement step, the node i will be incorrectly clustered given the current estimation of the partition $z^{(t)}$ at time t ”. This corresponds to the condition

$$a \neq \arg \min_k \|X_i - \mu_k^{(t)}\|^2 + \hat{\lambda}^{(t)} \|A_i \cdot W^{(t)} - \Pi_k^{(t)}\|^2$$

for a node i such that $z_i = a$. One can see that this condition is equivalent to the existence of $b \in [K] \setminus a$ such that

$$\underbrace{\langle \epsilon_i, \tilde{\mu}_a - \tilde{\mu}_b \rangle + \lambda \langle E_i; W, \tilde{\Pi}_a - \tilde{\Pi}_b \rangle}_{C_i(a,b)} \leq \frac{-\Delta^2(a,b)}{2} + Err_{ib}^{(t)}.$$

Here,

$$\begin{aligned}\Delta^2(a, b) &= \|\mu_a - \mu_b\|^2 + \lambda \|\Pi_{a\cdot} - \Pi_{b\cdot}\|^2, \\ \tilde{\mu}_k &= X^\top W_{\cdot a}, \tilde{\Pi}_{k\cdot} = W_{k\cdot}^\top AW, \\ \text{and } \lambda &= \frac{n_{min}}{p_{max}} \text{ or } \frac{n}{K(p-q)} \log \left(\frac{p(1-q)}{q(1-p)} \right)\end{aligned}$$

depending whether we are analyzing **sIR-LS** or **IR-LSS**. Moreover, $Err_{ib}^{(t)}$ is an error term that can be further decomposed as a sum $F_{ib}^{(t)} + G_{ib}^{(t)} + H_{ib}^{(t)}$ of different kinds of error terms which will be controlled in different ways. If we ignore the error term, we obtain the condition corresponding to having an incorrect result after one iteration starting from the ground truth partition. The errors occurring in this way will be quantified by the **ideal oracle error**

$$\xi(\delta) = \sum_{i=1}^n \sum_{b \in [K] \setminus z_i} \Delta^2(z_i, b) \mathbf{1}_{\{C_i(a,b) \leq \frac{-(1-\delta)\Delta^2(z_i,b)}{2}\}}.$$

Let us denote

$$\Delta_{min} = \min_{a \neq b \in [K]} \Delta(a, b)$$

to quantify the separation of the parameters associated with the different communities. If $\Delta_{min} = 0$, it would imply that at least two communities are indistinguishable and the model would not be identifiable. For $t \geq 1$ and $\delta \in [0, 1)$, let

$$\delta^{(t)} = \max\left(\frac{7}{8} \frac{\tau^{(t-1)}}{\tau^{(0)}}, \delta\right), \quad \tau^{(t)} = \tau^{(0)} \delta^{(t)}$$

be sequences where $\tau^{(0)} = \epsilon n \Delta_{min}^2 / K$ for a small enough constant $\epsilon > 0$.

In general the rate of decay of $\xi(\delta)$ leads to the convergence rate of iterative refinement algorithms, hence it is important to control this quantity.

Condition A (ideal error). *Assume that*

$$\xi(\delta^{(t)}) \leq \frac{3}{4} \tau^{(t-1)}, \text{ for all } t \geq 1$$

holds with probability at least $1 - \eta_1$.

We now have to analyze the error terms and prove that their contribution is negligible compared to the ideal oracle error rate. Let

$$l(z, z') = \sum_{i \in [n]} \Delta^2(z_i, z'_i) \mathbf{1}_{\{z_i \neq z'_i\}}$$

be a measure of distance between two partitions $z, z' \in [K]^n$. We will control the error terms by showing that the following conditions are satisfied.

Condition B (F-error type). *Assume that*

$$\max_{\{z^{(t)} : l(z, z^{(t)}) \leq \tau^{(0)}\}} \sum_{i=1}^n \max_{b \in [K] \setminus z_i} \frac{(F_{ib}^{(t)})^2}{\Delta^2(z_i, b) l(z, z^{(t)})} \leq \frac{\delta^2}{256}$$

for all $t \geq 0$ holds with probability at least $1 - \eta_2$.

Condition C (GH-error type). *Assume that*

$$\max_{i \in [n]} \max_{b \in [K] \setminus z_i} \frac{|H_{ib}^{(t)}| + |G_{ib}^{(t)}|}{\Delta(z_i, b)^2} \leq \frac{\delta^{(t)}}{4}$$

holds uniformly on the event $\{z^{(t)} : l(z, z^{(t)}) \leq \tau^{(t)}\}$ for all $t \geq 0$ with probability at least $1 - \eta_3$.

We can now show under these conditions that there is a contraction of the error if the initial estimate of the partition is close enough to the ground truth partition.

Theorem 1. *Assume that $l(z^{(0)}, z) \leq \tau^{(0)}$ and $\delta < 1$. Additionally assume that Conditions A, B, and C hold. Then with probability at least $1 - \sum_{i=1}^3 \eta_i$*

$$l(z^{(t)}, z) \leq \xi(\delta^{(t)}) + \frac{1}{8}l(z^{(t-1)}, z), \forall t \geq 1. \quad (4.1)$$

Remark 2. *This is an adaptation of Theorem 3.1 in Gao and Zhang (2019) where we allow at each step to choose a different $\delta^{(t)}$. It allows us to obtain a weaker condition for initialization than the one used in (Gao and Zhang, 2019, Theorem 4.1). Indeed, they require $l(z^{(0)}, z) = o(\frac{n\Delta_{min}^2}{K})$, but we only need $l(z^{(0)}, z) = O(\frac{n\Delta_{min}^2}{K})$.*

Proof of Theorem 1. By definition $\delta^{(t)} < 1$ for all $t \geq 1$. Let $i \in [n]$ such that $z_i = a$ and assume that $l(z^{(t-1)}, z) \leq \tau^{(t-1)}$ for some given $t \geq 1$. Denoting $I_i^{(t)}(a, b) := \mathbf{1}_{\{C_i(a,b) \leq \frac{-(1-\delta^{(t)})\Delta^2(a,b)}{2}\}}$, observe that

$$\begin{aligned} & \mathbf{1}_{\{z_i^{(t)}=b\}} \\ & \stackrel{(1)}{\leq} \mathbf{1}_{\{C_i(a,b) \leq \frac{-\Delta^2(a,b)}{2} + F_{ib}^{(t-1)} + G_{ib}^{(t-1)} + H_{ib}^{(t-1)}\}} \\ & \stackrel{(2)}{\leq} I_i^{(t)}(a, b) + \mathbf{1}_{\{\frac{\delta^{(t)}}{2}\Delta^2(a,b) \leq F_{ib}^{(t-1)} + G_{ib}^{(t-1)} + H_{ib}^{(t-1)}\}} \\ & \stackrel{(3)}{\leq} I_i^{(t)}(a, b) + \mathbf{1}_{\{\frac{\delta^{(t)}}{4}\Delta^2(a,b) \leq F_{ib}^{(t-1)}\}} \\ & \leq I_i^{(t)}(a, b) + \mathbf{1}_{\{\frac{\delta}{4}\Delta^2(a,b) \leq F_{ib}^{(t-1)}\}} \\ & \stackrel{(4)}{\leq} I_i^{(t)}(a, b) + \frac{32(F_{ib}^{(t-1)})^2}{\delta^2\Delta^4(a, b)}. \end{aligned}$$

The inequality (1) follows from the definition of $z_i^{(t)}$ and the error decomposition. Inequality (2) comes from a union bound while (3) uses Condition C. Finally, (4) follows from Markov inequality. Hence,

$$\begin{aligned} l(z^{(t)}, z) &= \sum_{i \in [n]} \sum_{b \in [K] \setminus \{z_i\}} \Delta^2(z_i, b) \mathbf{1}_{\{z_i^{(t)}=b\}} \\ &\leq \sum_{i \in [n]} \sum_{b \in [K] \setminus \{z_i\}} \Delta^2(z_i, b) \mathbf{1}_{\{C_i(a,b) \leq \frac{-(1-\delta^{(t)})\Delta^2(z_i,b)}{2}\}} \\ &\quad + \sum_{i \in [n]} \sum_{b \in [K] \setminus \{z_i\}} \Delta^2(z_i, b) \mathbf{1}_{\{z_i^{(t)}=b\}} \frac{32(F_{ib}^{(t-1)})^2}{\delta^2\Delta^4(z_i, b)} \\ &\leq \xi(\delta^{(t)}) + \sum_{i \in [n]} \max_{b \in [K] \setminus \{z_i\}} \frac{32(F_{ib}^{(t-1)})^2}{\delta^2\Delta^2(z_i, b)} \\ &\leq \xi(\delta^{(t)}) + \frac{1}{8}l(z^{(t-1)}, z). \end{aligned}$$

Using Condition A, we hence obtain

$$l(z^{(t)}, z) \leq \xi(\delta^{(t)}) + \frac{1}{8}\tau^{(t-1)} \leq \frac{7}{8}\tau^{(t-1)}.$$

Thus $\tau^{(t)}$ is an upper bound for $l(z^{(t)}, z)$ and the theorem is proved by induction. \square

By iteratively unwrapping (4.1) we obtain for t large enough the following bound on $l(z^{(t)}, z)$.

Corollary 1. *Under the assumptions of Theorem 1, we have for all $t \gtrsim \log(1/\delta)$ that*

$$l(z^{(t)}, z) \lesssim \xi(\delta) + \tau^{(0)}(1/8)^{t-\Theta(\log(1/\delta))}.$$

4.2 Convergence guarantees for IR-LSS under the CSSBM

Let us define the SNR

$$\tilde{\Delta}^2 = \frac{1}{8} \min_{k \neq k'} \|\mu_k - \mu_{k'}\|^2 + \frac{\log n}{K} (\sqrt{p'} - \sqrt{q'})^2.$$

It is easy to see that $\tilde{\Delta} \asymp \Delta_{\min}$. The following lemma shows that $\xi(\delta)$ decreases exponentially fast in $\tilde{\Delta}$ provided Δ_{\min} is suitably large.

Lemma 1. *Assume that $K^{1.5}/\Delta_{\min} \rightarrow 0$ and $\delta = \delta(n) \rightarrow 0$ at a suitably slow rate. Then with probability at least $1 - \exp(-\tilde{\Delta})$, we have*

$$\xi(\delta) \leq n \exp(-(1 + o(1))\tilde{\Delta}^2).$$

The following theorem shows that if $z^{(0)}$ is close enough to z , then the misclustering rate decreases exponentially fast with the SNR $\tilde{\Delta}$ after $O(\log n)$ iterations.

Theorem 2. *Assume that $K^{1.5}/\Delta_{\min} \rightarrow 0$ and $\tilde{\Delta}^2 \asymp \log n/K$. Under the CSSBM(p, q, n, K) assumption, if $z^{(0)}$ is such that*

$$l(z, z^{(0)}) \leq \frac{\epsilon n \Delta_{\min}^2}{K}$$

for a constant ϵ small enough, then with probability at least $1 - n^{-\Omega(1)}$ we have for all $t \gtrsim \log n$

$$r(z^{(t)}, z) \leq \exp(-(1 + o(1))\tilde{\Delta}^2).$$

Sketch of proof. We first show that Conditions B and C are satisfied. Then we show that Condition A is satisfied for the sequences $\delta^{(t)}$ and $\tau^{(t)}$, hence Theorem 1 can be applied to obtain a contraction of the error at each step. \square

Remark 3. *By assumption $\tilde{\Delta}^2 \gtrsim \log n/K$, and so the condition $\tilde{\Delta}^2 \asymp \log n/K$ is not very restrictive. Indeed, if the information provided by the GMM part was not of the same order as the graph part, it would not be useful to aggregate information. If $\tilde{\Delta}^2 \gg \log n$ then we would be in the exact recovery setting and the problem becomes easy.*

4.3 Minimax lower-bound for CSSBM

We are going to establish that the convergence rate established in Theorem 2 is optimal. Let

$$\Theta = \{(\mu_k)_{k \in [K]} \in \mathbb{R}^K, p, q \in [0, 1] \text{ such that } p > q\}$$

be the admissible parameter space.

Theorem 3. *Under the assumption $\tilde{\Delta}/\log K \rightarrow \infty$, we have*

$$\inf_{\hat{z}} \sup_{\theta \in \Theta} \mathbb{E}(r(\hat{z}, z)) \geq \exp(-(1 + o(1))\tilde{\Delta}^2).$$

If $\tilde{\Delta} + \log K = O(1)$, then $\inf_z \sup_{\theta \in \Theta} \mathbb{E}(\frac{r(\hat{z}, z)}{n}) \geq c$ for some positive constant c .

Remark 4. *This lower-bound shows that if $\tilde{\Delta}^2 < \log n$ then every estimator fails to achieve exact recovery with a probability bounded below from zero because $\sup_{\theta \in \Theta} \mathbb{E}(r(\hat{z}, z)) > n^\epsilon$ for some $\epsilon > 0$. On the other hand, Theorem 2 shows that when $\tilde{\Delta}^2 > \log n$ then IR-LSS achieves exact recovery. Hence the threshold for exact recovery is $\tilde{\Delta}^2/\log n$. When $K = 2$ and $\mu_1 = -\mu_2 = \mu$ this matches the result obtained by Abbe et al. (2020).*

Sketch of proof. We can use the same argument as in (Lu and Zhou, 2016, Theorem 3.3) to reduce the problem to a hypothesis testing problem. The solution of the latter is given by the maximum likelihood test according to the Neyman-Pearson lemma. Then the probability of error can be controlled by using concentration inequalities. \square

4.4 Convergence guarantees for sIR-LS

The proof techniques used in the previous section can be extended in a straightforward way to obtain consistency results for sIR-LS under the CSBM. The main difference is that the specialized concentration inequality used to prove Lemma 1 can no longer be applied to this setting.

Theorem 4. *Assume that $K^{1.5}/\Delta_{min} \rightarrow 0$, $\Delta_{min}^2 \asymp \log n/K$ and $\max_{a,b \in [K]} \Delta^2(a,b) \lesssim \Delta_{min}^2$. Under the CSBM with approximately balanced communities, if*

$$l(z, z^{(0)}) \leq \frac{\epsilon n \Delta_{min}^2}{K}$$

for some small enough constant $\epsilon > 0$, then with probability at least $1 - n^{-\Omega(1)}$ we have for all $t \gtrsim \log n$

$$r(z^{(t)}, z) \leq \exp\left(-\frac{1}{8}\Delta_{min}^2\right).$$

5 Numerical experiments

We now empirically evaluate our method on both synthetic and real data. Section 5.1 contains simulations for the CSBM and Section 5.2 contains results for clustering signed networks under a Signed SBM. In Section 5.3, we test our method on a dataset consisting of a (weighted) signed graph along with covariate information for the nodes.

5.1 CSBM with not well separated communities

In this experiment the graph is generated from a SBM with parameters $n = 1000$, $K = 3$, $Z_i \stackrel{i.i.d}{\sim}$ Multinomial(1; 1/3, 1/3, 1/3), and

$$\Pi = 0.02 * \begin{pmatrix} 1.6 & 1.2 & 0.5 \\ 1.2 & 1.6 & 0.5 \\ 0.05 & 0.05 & 1.2 \end{pmatrix}.$$

The covariates are generated from a GMM with variance $\sigma^2 = 0.2$ and class centers $\mu_1 = (0, 0, 1)$, $\mu_2 = (-1, 1, 0)$, $\mu_3 = (0, 0, 1)$. Note that $\mathcal{C}_1, \mathcal{C}_3$ cannot be separated by the covariate information, while $\mathcal{C}_1, \mathcal{C}_2$ are not well separated in the graph information (as seen from Π). Hence, one would expect in this example that using only a single source of information should not yield good clustering results. To demonstrate this, we use the Normalized Mutual Information (NMI) criterion to measure the quality of the resulting clusters. It is an information theoretic measure of similarity taking values in $[0, 1]$, with 1 denoting a perfect match, and 0 denoting the absence of correlation between partitions.

Performance comparison. We will use K-SC and L-SC to denote respectively the results obtained by applying spectral clustering on the Gaussian kernel matrix K formed from the covariates, and spectral clustering (SC) applied on the Laplacian of the graph. Additionally, SDP-Comb refers to the method proposed by Yan and Sarkar (2020); IR-MAP is similar to IR-LS but with the least-square criterion replaced by the MAP to update the partition; ORL-SC (Oracle Regularized Laplacian SC) corresponds to SC applied on $A + \lambda K$ where λ is chosen to maximize the NMI between the (oracle known) true partition and the one obtained by using SC on $A + \lambda K$. For the implementation of SDP-Comb, we used the Matlab code provided by Yan and Sarkar (2020) with the λ given by ORL-SC. Figure 1 shows that the three iterative methods considered (IR-MAP, IR-LS, sIR-LS), initialized with EM-Emb, provide significantly better clustering performance compared to the other methods. The variance of sIR-LS is a bit larger than IR-LS and it also seems that sIR-LS IR-MAP are more sensitive to initialization (i.e., more outliers). On the other hand, other methods based on the aggregation of the two sources of information (SDP-Comb and ORL-SC) lead to a limited improvement in clustering performance.

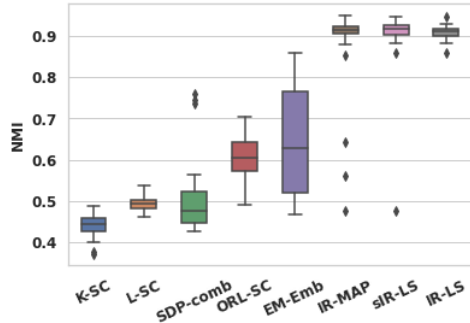


Figure 1: Average performance over 40 runs of different algorithms under CSBM.

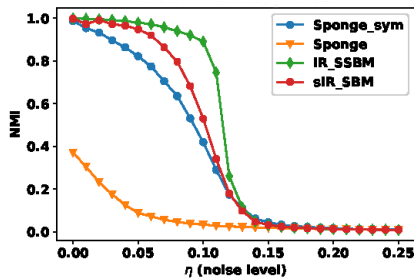


Figure 2: NMI versus η (noise) under signed SBM, $K = 20$, $n = 10000$, $p = 0.01$.

Computational cost. We took the average of CPU time (in seconds) over 20 repetitions. There is an important gain in speed obtained by replacing the MAP objective by a least square criterion. Moreover, the initialization obtained with EM-Emb is very fast. The results are gathered in Table 1.

	L-SC	ORL-SC	EM-Emb	IR-LS	IR-MAP
Time	1.4	7.9	0.5	1.2	37.1
Ratio	2.7	15	1	2.3	70

Table 1: Comparison between computation times (averaged over 20 runs)

5.2 Signed SBM

A graph is generated from the Signed SBM as follows. First we generate an Erdős-Renyi graph where each edge appears with probability p and each edge takes the value 1 if both extremities are in the same community and -1 otherwise. Then we flip the sign of each edge independently with probability $\eta \in [0, 1/2)$. Our method sIR-LS can be directly applied to this setting, but we can also use the fact that the connectivity matrix Π is assortative to design a more specialised algorithm IR-SSBM (see appendix) that assigns a node to the community which maximizes its intra-connectivity estimated probability. For initialization, we use Sponge-sym (Cucuringu et al., 2019) for clustering signed graphs. Figure 2 shows that 20 refinement steps improves the clustering.

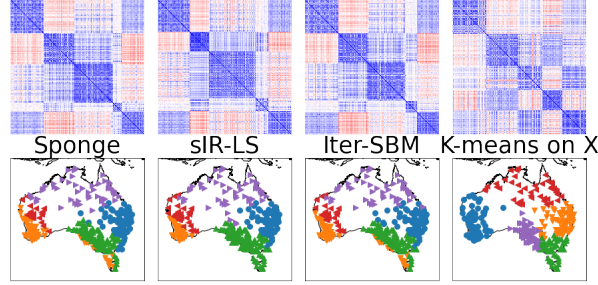


Figure 3: Sorted adjacency matrices and maps for Australian rainfall dataset ($K = 5$).

5.3 Australia Rainfall Dataset

We consider the time series data of historical rainfalls in locations throughout Australia, this was also studied in Cucuringu et al. (2019). Edge weights are obtained from the pairwise Pearson correlation, leading to a complete signed graph on $n = 306$ nodes. We use the longitude and latitude as covariates X , and **Sponge** (Cucuringu et al., 2019) to obtain an initial partition for **sIR-LS** and **Iter-SBM** (the version of **sIR-LS** without covariates). We exclude **IR-LS** here due to its relative instability on this dataset (see appendix). This shows that in some situations it can be better to use **sIR-LS** rather than **IR-LS**. Figure 3 illustrates the clustering obtained with **Sponge** (using only the graph), **sIR-LS** (integrating the covariates), **Iter-SBM** (refinement without covariates), and **K-means** applied on the covariates. The use of covariates in the refinement steps reinforces the geographical structure (orange points in the bottom right part of the map disappeared), increases the size of smallest cluster (the violet cluster on the three first maps), and strengthens the original clustering as seen in the sorted adjacency matrix, whereas **Iter-SBM** ignores the geography and **K-means** ignores the graph structure. Results for other choices of K are in the appendix.

6 Future work

We only analyzed **sIR-LS** and **IR-LSS** to reduce technicalities but we believe that the framework can be extended to analyze **IR-LS**. The principle we used to design our algorithm could also be applied to obtain a clustering method for bipartite graphs or multilayer networks. Another direction of research is to extend our method to more general graph models integrating common properties of real-life networks such as degree heterogeneity, mixed membership, presence of outliers and missing values.

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Supplementary Material

The proof of Corollary 1 is presented in Section A and the proof of Lemma 1 is presented in Section B. Theorem 2 is proved in Section C and Theorem 3 is proved in Section D. The technical lemmas used in the proofs are gathered in Section E. Finally, Section F contains additional experiments results.

A Proof of Corollary 1

We will prove a more precise version of Corollary 1 stated below.

Corollary 2. *Assume that the assumptions of Theorem 1 hold. Denoting $t^* = \lceil \frac{\log(1/\delta)}{\log(8/7)} \rceil$, we have for all $t \geq t^*$ that $\tau^{(t)} = \tau$, $\delta^{(t)} = \delta$ and*

$$l(z^{(t)}, z) \leq \frac{8}{7}\xi(\delta) + \frac{3}{28}\tau^{(0)} \left(\frac{1}{8}\right)^{t-t^*}$$

Proof. For convenience, denote $\tau = \tau^{(0)}\delta$. Let t^* be the smallest integer such that $\tau \geq \left(\frac{7}{8}\right)^{t^*}\tau^{(0)}$; clearly, $t^* = \lceil \frac{\log(1/\delta)}{\log(8/7)} \rceil$. Then for $t \geq t^*$, we have $\tau^{(t)} = \tau = \tau^{(0)}\delta$, and hence (from the definition of $\delta^{(t)}$), $\delta^{(t)} = \delta$. Therefore Theorem 1 implies that for $t \geq t^*$,

$$\begin{aligned} l(z^{(t)}, z) &\leq \xi(\delta^{(t)}) + \frac{1}{8}\xi(\delta^{(t-1)}) + \dots + \left(\frac{1}{8}\right)^{t-t^*} \xi(\delta^{(t^*)}) + \left[\left(\frac{1}{8}\right)^{t-t^*+1} \xi(\delta^{(t^*-1)}) + \dots + \left(\frac{1}{8}\right)^{t-1} \xi(\delta^{(1)}) \right] \\ &\leq \frac{8}{7}\xi(\delta) + \left[\left(\frac{1}{8}\right)^{t-t^*+1} \xi(\delta^{(t^*-1)}) + \dots + \left(\frac{1}{8}\right)^{t-1} \xi(\delta^{(1)}) \right] \quad (\text{since } \delta^{(t)} = \delta \text{ for } t \geq t^*) \\ &\leq \frac{8}{7}\xi(\delta) + \frac{3}{4}\tau^{(0)} \left[\left(\frac{1}{8}\right)^{t-1} + \dots + \left(\frac{1}{8}\right)^{t-t^*+1} \right] \quad (\text{since for all } t, \xi(\delta^{(t)}) \leq \frac{3}{4}\tau^{(0)} \text{ by Condition A}) \\ &\leq \frac{8}{7}\xi(\delta) + \frac{3}{28}\tau^{(0)} \left(\frac{1}{8}\right)^{t-t^*}. \end{aligned}$$

□

B Proof of Lemma 1

Let $\delta, \bar{\delta} > 0$. The ideal oracle error term can be upper bounded as follows

$$\begin{aligned} \xi(\delta) &\leq \underbrace{\sum_{i=1}^n \sum_{b \in [K] \setminus z_i} \Delta^2(z_i, b) \mathbf{1}_{\{\langle \epsilon_i, \mu_{z_i} - \mu_b \rangle + \lambda \langle E_i, W, \Pi_{z_i}, -\Pi_b \rangle \leq \frac{-(1-\delta-\bar{\delta})\Delta^2(z_i, b)}{2}\}}}_{M_1} \\ &+ \underbrace{\sum_{i=1}^n \sum_{b \in [K] \setminus z_i} \Delta^2(z_i, b) \mathbf{1}_{\{\langle \epsilon_i, \tilde{\mu}_{z_i} - \mu_{z_i} \rangle + \lambda \langle E_i, W, \tilde{\Pi}_{z_i}, -\Pi_{z_i} \rangle \leq \frac{-\bar{\delta}\Delta^2(z_i, b)}{4}\}}}_{M_2} \\ &+ \underbrace{\sum_{i=1}^n \sum_{b \in [K] \setminus z_i} \Delta^2(z_i, b) \mathbf{1}_{\{\langle -\epsilon_i, \tilde{\mu}_b - \mu_b \rangle - \lambda \langle E_i, W, \tilde{\Pi}_b, -\Pi_b \rangle \leq \frac{-\bar{\delta}\Delta^2(z_i, b)}{4}\}}}_{M_3}. \end{aligned}$$

We will first obtain upper bounds for each $\mathbb{E}(M_i)$, $i = 1 \dots 3$. In particular we will show that the dominant term is $\mathbb{E}(M_1)$. Then, we will use Markov inequality to control $\xi(\delta)$ with high probability.

Upper bound of $\mathbb{E}(M_1)$. Let us denote for any given $i \in [n]$ and $b \in [K] \setminus z_i$ the event

$$\Omega_1 = \left\{ \langle \epsilon_i, \mu_{z_i} - \mu_b \rangle + \lambda \langle E_i, W, \Pi_{z_i} - \Pi_b \rangle \leq \frac{-(1 - \delta - \bar{\delta}) \Delta^2(z_i, b)}{2} \right\}.$$

By using an analogous argument as the one presented in Lemma 10 we obtain

$$\mathbb{P}(\Omega_1) \leq \exp(-(1 + o(1)) \tilde{\Delta}^2).$$

Thus by taking $\delta = \bar{\delta}$ going to zero as $n \rightarrow \infty$, we obtain

$$\begin{aligned} \mathbb{E}(M_1) &\leq \sum_{i=1}^n \sum_{b \in [K] \setminus z_i} \Delta^2(z_i, b) \exp(-(1 + o(1)) \tilde{\Delta}^2) \\ &\leq nK \exp(-(1 + o(1)) \tilde{\Delta}^2) \\ &\leq n \exp(-(1 + o(1)) \tilde{\Delta}^2). \end{aligned}$$

In the second line we used the fact that $\Delta^2(z_i, b) = \Delta_{min} \lesssim \tilde{\Delta}^2$ for all $z_i \neq b$ and $\tilde{\Delta} \asymp \sqrt{\log n/K} \rightarrow \infty$. In the third line we used the assumption $\tilde{\Delta}^2 / \log(K) \rightarrow \infty$.

Upper bound of $\mathbb{E}(M_2)$. Let us denote for any given $i \in [n]$ and $b \in [K] \setminus z_i$ the events

$$\Omega_2 = \left\{ \langle \epsilon_i, \tilde{\mu}_{z_i} - \mu_{z_i} \rangle + \lambda \langle E_i, W, \tilde{\Pi}_{z_i} - \Pi_{z_i} \rangle \leq \frac{-\bar{\delta} \Delta^2(z_i, b)}{4} \right\},$$

$$\Omega'_2 = \left\{ \langle \epsilon_i, \tilde{\mu}_{z_i} - \mu_{z_i} \rangle \leq \frac{-\bar{\delta} \Delta^2(z_i, b)}{8} \right\},$$

and

$$\Omega''_2 = \left\{ \lambda \langle E_i, W, \tilde{\Pi}_{z_i} - \Pi_{z_i} \rangle \leq \frac{-\bar{\delta} \Delta^2(z_i, b)}{8} \right\}.$$

Clearly $\mathbb{P}(\Omega_2) \leq \mathbb{P}(\Omega'_2) + \mathbb{P}(\Omega''_2)$ by a union bound argument.

Let us first upper bound $\mathbb{P}(\Omega'_2)$. Recall that $n_k = n/K$ under the CSSBM by assumption, let us also define $n_{min} := \min_k n_k$. We keep this general notation because it is shorter and indicates how the proof can be generalized to the unbalanced setting. By definition $\tilde{\mu}_{z_i} - \mu_{z_i} = \sum_{j \in \mathcal{C}_{z_i}} \frac{\epsilon_j}{n_{z_i}}$, hence

$$\langle \epsilon_i, \tilde{\mu}_{z_i} - \mu_{z_i} \rangle = \frac{\|\epsilon_i\|^2 + \epsilon_i^\top \sum_{j \in \mathcal{C}_{z_i}, j \neq i} \epsilon_j}{n_{z_i}}.$$

This last quantity is lower bounded by $\epsilon_i^\top \eta_i$ where $\eta_i = \frac{\sum_{j \in \mathcal{C}_{z_i}, j \neq i} \epsilon_j}{n_{z_i}}$. In particular ϵ_i and η_i are independent and their entries are also independent. Moreover η_i is a centered gaussian random variables with independent entries such that $\text{Var}((\eta_i)_k) \leq 1/n_k$. So by Bernstein inequality, it holds for all $x > 0$ that

$$\mathbb{P} \left(\|\eta_i\|^2 \geq \frac{1}{n_k} (K + 2\sqrt{Kx} + 2x) \right) \leq \exp(-x)$$

which in turn implies

$$\begin{aligned} \mathbb{P} \left(\epsilon_i^\top \eta_i \leq -\frac{\bar{\delta} \Delta_{min}^2}{8} \right) &\leq \mathbb{P} \left(\epsilon_i^\top \eta_i \leq -\frac{\bar{\delta} \Delta_{min}^2}{8} \mid \|\eta_i\|^2 \leq \frac{1}{n_k} (K + 2\sqrt{Kx} + 2x) \right) \\ &\quad + \mathbb{P} \left(\|\eta_i\|^2 \geq \frac{1}{n_k} (K + 2\sqrt{Kx} + 2x) \right) \\ &\leq \exp \left(-c \frac{n_k (\bar{\delta} \Delta_{min}^2)^2}{K + 2\sqrt{Kx} + 2x} \right) + \exp(-x). \end{aligned}$$

Setting $x = \sqrt{n_k \bar{\delta} \Delta_{min}^2}$ we obtain $\mathbb{P}(\Omega'_2) \leq 2 \exp(-C \bar{\delta} \sqrt{n_k} \Delta_{min}^2)$. Since $\bar{\delta} \rightarrow 0$ (as $n \rightarrow \infty$) at a suitably slow rate, we have $\bar{\delta} \sqrt{n/K} \rightarrow +\infty$. Consequently,

$$\mathbb{P}(\Omega'_2) = o(\exp(-(C + o(1))\Delta_{min}^2)) = o(\exp(-(1 + o(1))\tilde{\Delta}^2)).$$

Let us now bound $\mathbb{P}(\Omega''_2)$. Since $\tilde{\Pi}_{kk'} - \Pi_{kk'} = \sum_{i \in \mathcal{C}_k, j \in \mathcal{C}_{k'}} \frac{E_{ij}}{n_k n_{k'}} = W_{:k}^\top E W_{:k'}$, we obtain the decomposition

$$\lambda \langle E_{i:} W, \tilde{\Pi}_{z_i:} - \Pi_{z_i:} \rangle = \lambda \langle E_{i:} W, W_{z_i:}^\top E^{(i)} W \rangle + \lambda \langle E_{i:} W, W_{z_i:}^\top E^{(-i)} W \rangle$$

where $E^{(i)}$ is obtained from E by only keeping the i th row and column, and E_{-i} is the matrix obtained from E by replacing the i th row and column by zero. In particular, $E^{(-i)}$ is independent from $E_{i:}$. The second term can be controlled by using the same techniques as before. Indeed, the entries of $W_{z_i:}^\top E^{(-i)} W$ are independent and $\text{Var}(W_{z_i:}^\top E^{(-i)} W_{:k}) \leq C \frac{p_{max}}{n_{min}^2}$ for all k . Denoting $\eta'_{ik} = W_{z_i:}^\top E^{(-i)} W_{:k}$ and $\eta'_i = (\eta'_{ik})_{k \in [K]}$, this implies

$$\begin{aligned} \mathbb{P} \left(\lambda \langle E_{i:} W, \eta'_i \rangle \leq -\frac{\bar{\delta} \Delta_{min}^2}{16} \right) &\leq \mathbb{P} \left(\lambda \langle E_{i:} W, \eta'_i \rangle \leq -\frac{\bar{\delta} \Delta_{min}^2}{16} \mid \forall k, |\eta'_{ik}|^2 \leq C \frac{p_{max}}{n_k^2} (K + x) \right) \\ &\quad + \mathbb{P} \left(\exists k, |\eta'_{ik}|^2 \geq C \frac{p_{max}}{n_{min}^2} (K + x) \right) \\ &\leq K \exp \left(-C \frac{n_{min}^3 (\bar{\delta} \Delta_{min}^2)^2}{p_{max} \lambda^2 (K + x)} \right) + K \exp(-x). \end{aligned}$$

Here, we used a union bound argument for the first inequality. The second inequality uses Lemma 8 – which provides a concentration bound for binomial random variables – along with the fact $\lambda \asymp \frac{n}{K p_{max}}$.

Setting $x = C \sqrt{n_k p_{max} \bar{\delta} \Delta_{min}^2}$ we obtain

$$\mathbb{P} \left(\lambda \langle E_{i:} W, \eta'_i \rangle \leq -\frac{\bar{\delta} \Delta_{min}^2}{16} \right) \leq 2 \exp(-c \sqrt{n_k p_{max} \bar{\delta} \Delta_{min}^2}) = o(\exp(-\tilde{\Delta}^2))$$

since $\bar{\delta}$ can be chosen such that $\sqrt{n_k p_{max} \bar{\delta}} \rightarrow +\infty$ (because by assumption $n p_{max} \asymp \log n \gg K^4$) and $\Delta_{min} \asymp \tilde{\Delta}$.

It remains to control $\langle E_{i:} W, W_{z_i:}^\top E^{(i)} W \rangle$. Using the fact

$$(W_{z_i:}^\top E^{(i)} W)_k = \begin{cases} \sum_{j' \in \mathcal{C}_k} \frac{E_{ij'}}{n_{z_i} n_k} & \text{if } k \neq z_i \\ 2 \sum_{j' \in \mathcal{C}_k} \frac{E_{ij'}}{n_{z_i}^2} & \text{if } k = z_i \end{cases}$$

we have

$$\begin{aligned} \langle E_{i:} W, W_{z_i:}^\top E^{(i)} W \rangle &= \sum_{k \neq z_i} \sum_{\substack{j \in \mathcal{C}_k \\ j' \in \mathcal{C}_k}} \frac{E_{ij}}{n_k} \frac{E_{ij'}}{n_{z_i} n_k} + 2n_{z_i} \left(\sum_{j \in \mathcal{C}_{z_i}} \frac{E_{ij'}}{n_{z_i}^2} \right)^2 \\ &= \frac{1}{n_{z_i}} \left(\sum_{j \in \mathcal{C}_k} \frac{E_{ij}}{n_k} \right)^2 + 2n_{z_i} \left(\sum_{j \in \mathcal{C}_{z_i}} \frac{E_{ij'}}{n_{z_i}^2} \right)^2 \\ &\geq 0. \end{aligned}$$

Consequently, $\mathbb{P}(\Omega''_2)$ can be bounded as

$$\mathbb{P}(\Omega''_2) \leq \mathbb{P} \left(\lambda \langle E_{i:} W, \eta'_i \rangle \leq -\frac{\bar{\delta} \Delta_{min}^2}{16} \right) = o(\exp(-\tilde{\Delta}^2)).$$

Upper bound of $\mathbb{E}(M_3)$. Let us denote for any given $i \in [n]$ and $b \in [K] \setminus z_i$ the event

$$\Omega_3 = \left\{ \langle -\epsilon_i, \tilde{\mu}_b - \mu_b \rangle - \lambda \langle E_i, W, \tilde{\Pi}_b - \Pi_b \rangle \leq \frac{-\bar{\delta} \Delta^2(z_i, b)}{4} \right\}.$$

First observe that

$$\langle \epsilon_i, \tilde{\mu}_b - \mu_b \rangle = \frac{\epsilon_i^\top \sum_{j \in \mathcal{C}_b} \epsilon_j}{n_{z_i}},$$

therefore this term can be handled in the same way as before. Moreover, we have

$$\lambda \langle E_i, W, \tilde{\Pi}_b - \Pi_b \rangle = \lambda \langle E_i, W, W_b^\top E^{(i)} W \rangle + \lambda \langle E_i, W, W_b^\top E^{(-i)} W \rangle.$$

The second term can be handled in the same way as before by using a conditioning argument. Now observe that

$$\langle E_i, W, W_b^\top E^{(i)} W \rangle = \frac{1}{n_{z_i}^2 n_b} \left(\sum_{j \in \mathcal{C}_b} E_{ij} \right) \left(\sum_{j' \in \mathcal{C}_{z_i}} E_{ij'} \right)$$

where $\sum_{j \in \mathcal{C}_b} E_{ij}$ and $\sum_{j' \in \mathcal{C}_{z_i}} E_{ij'}$ are independent subgaussian random variables. Thus this term can also be controlled by using the same conditioning argument as before.

Conclusion. The previously obtained upper bounds imply

$$\mathbb{E}(\xi(\delta)) \leq 3\mathbb{E}(M_1) \leq n \exp(-(1 + o(1))\tilde{\Delta}^2).$$

Finally, by Markov inequality, we obtain

$$\mathbb{P}(\xi(\delta) \geq \exp(\tilde{\Delta})\mathbb{E}\xi(\delta)) \leq \exp(-\tilde{\Delta}).$$

But since

$$\exp(\tilde{\Delta})\mathbb{E}\xi(\delta) \leq n \exp(-(1 + o(1))\tilde{\Delta}^2)$$

we obtain that with probability at least $1 - \exp(-\tilde{\Delta})$

$$\xi(\delta) \leq n \exp(-(1 + o(1))\tilde{\Delta}^2).$$

C Proof of Theorem 2

The general proof strategy has been presented in Section 4.1. In Section C.1 we will make the error decomposition explicit. Then, we will control the different error terms in Sections C.2, C.3 and C.4. Finally, we will conclude by applying Theorem 1 in Section C.5.

C.1 Error decomposition for the one-step analysis of IR-LSS

We will assume without loss of generality that $\sigma = 1$ to simplify the exposition. Let $i \in [n]$ and $a \in [K]$ be such that¹ $z_i = a$, and let

$$\lambda^{(t)} = \frac{n}{K(p^{(t)} - q^{(t)})} \log \left(\frac{p^{(t)}(1 - q^{(t)})}{q^{(t)}(1 - p^{(t)})} \right)$$

denote the scalar corresponding to the diagonal entry of the inverse covariance matrix $\Sigma_k^{(t)}$. Similarly, let us denote

$$\lambda = \frac{n}{K(p - q)} \log \left(\frac{p(1 - q)}{q(1 - p)} \right).$$

¹Depending on the context we will interchangeably use the notation z_i and a .

Given the current estimator of the partition $Z^{(t)}$, node i will be incorrectly estimated after one refinement step if

$$a \neq \arg \min_k \|X_i - \mu_k^{(t)}\|^2 + \hat{\lambda}^{(t)} \|A_i:W^{(t)} - \Pi_k^{(t)}\|^2$$

or equivalently, if there exists $b \in [K] \setminus a$ such that

$$\|X_i - \mu_b^{(t)}\|^2 + \hat{\lambda}^{(t)} \|A_i:W^{(t)} - \Pi_b^{(t)}\|^2 \leq \|X_i - \mu_a^{(t)}\|^2 + \hat{\lambda}^{(t)} \|A_i:W^{(t)} - \Pi_a^{(t)}\|^2.$$

The above inequality is equivalent to

$$\langle \epsilon_i, \tilde{\mu}_a - \tilde{\mu}_b \rangle + \lambda \langle E_i:W, \tilde{\Pi}_a - \tilde{\Pi}_b \rangle \leq \frac{-\Delta^2(a, b)}{2} + F_{ib}^{(t)} + G_{ib}^{(t)} + H_{ib}^{(t)}$$

where

$$\Delta^2(a, b) = \|\mu_a - \mu_b\|^2 + \lambda \|\Pi_a - \Pi_b\|^2, \quad \tilde{\mu}_k = X^\top W_{:a}, \quad \text{and} \quad \tilde{\Pi}_k = W_k^\top AW$$

for all $k \in [K]$. Furthermore, the terms $F_{ib}^{(t)}$, $G_{ib}^{(t)}$ and $H_{ib}^{(t)}$ are given by

$$\begin{aligned} F_{ib}^{(t)} &= \langle \epsilon_i, (\tilde{\mu}_a - \mu_a^{(t)}) - (\tilde{\mu}_b - \mu_b^{(t)}) \rangle + \lambda^{(t)} \langle E_i:W^{(t)}, (\tilde{\Pi}_a - \Pi_a^{(t)}) - (\tilde{\Pi}_b - \Pi_b^{(t)}) \rangle \\ &\quad + \lambda^{(t)} \langle E_i:(W - W^{(t)}), \tilde{\Pi}_a - \tilde{\Pi}_b \rangle + (\lambda - \lambda^{(t)}) \langle E_i:W, \tilde{\Pi}_a - \tilde{\Pi}_b \rangle, \\ 2G_{ib}^{(t)} &= (\|\mu_a - \mu_a^{(t)}\|^2 - \|\mu_a - \tilde{\mu}_a\|^2) - (\|\mu_b - \mu_b^{(t)}\|^2 - \|\mu_b - \tilde{\mu}_b\|^2) \\ &\quad + \lambda^{(t)} (\|P_i:W^{(t)} - \Pi_a^{(t)}\|^2 - \|P_i:W^{(t)} - W_a^\top AW^{(t)}\|^2) \\ &\quad - \lambda^{(t)} (\|P_i:W^{(t)} - \Pi_b^{(t)}\|^2 - \|P_i:W^{(t)} - W_b^\top AW^{(t)}\|^2) \\ \text{and } 2H_{ib}^{(t)} &= \|\mu_a - \tilde{\mu}_a\|^2 - \|\mu_a - \tilde{\mu}_b\|^2 + \|\mu_a - \mu_b\|^2 \\ &\quad + \lambda^{(t)} (\|P_i:W^{(t)} - W_a^\top AW^{(t)}\|^2 - \|P_i:W^{(t)} - W_b^\top AW^{(t)}\|^2 + \|\Pi_a - \Pi_b\|^2) \\ &\quad + (\lambda - \lambda^{(t)}) \|\Pi_a - \Pi_b\|^2. \end{aligned}$$

The main term in this decomposition is

$$\langle \epsilon_i, \tilde{\mu}_a - \tilde{\mu}_b \rangle + \lambda \langle E_i:W, \tilde{\Pi}_a - \tilde{\Pi}_b \rangle \leq \frac{-\Delta^2(a, b)}{2}$$

and corresponds to the error when the current estimation of the partition is the ground truth partition. It is controlled by Lemma 1

The three error terms will be controlled in different ways. The error term $F_{ib}^{(t)}$ depends in a crucial way on i and t , it will be controlled with a l_2 -type norm (see Condition B). The square of the error terms $G_{ib}^{(t)}$ and $|H_{ib}^{(t)}|$ will be controlled uniformly (see Condition C).

Lemma 2. *Under the assumptions of Theorem 4 (that are also satisfied by Theorem 2) we have w.h.p. that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$,*

$$\max_{i \in [n]} \max_{b \in [K] \setminus z_i} \frac{|H_{ib}^{(t)}|}{\Delta^2(z_i, b)^2} \leq \frac{\delta^{(t)}}{8}$$

C.2 Bounding the error term $F_{ib}^{(t)}$

In this section we are going to show that Condition B is satisfied.

Lemma 3. *Under the assumptions of Theorem 4 (that are also satisfied by Theorem 2) we have w.h.p. that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(0)}$,*

$$\sum_{i=1}^n \max_{b \in [K] \setminus z_i} \frac{(F_{ib}^{(t)})^2}{\Delta^2(z_i, b) l(z, z^{(t)})} \leq \frac{\delta^2}{256}.$$

Proof. We need to upper-bound of

$$F = \max_{\{z^{(t)}: l(z, z^{(t)}) \leq \tau^{(0)}\}} \sum_{i=1}^n \max_{b \in [K] \setminus z_i} \frac{(F_{ib}^{(t)})^2}{\Delta(z_i, b)^2 l(z, z^{(t)})}.$$

To this end, we can decompose $F_{ib}^{(t)} = F_{ib}^{1,(t)} + F_{ib}^{2,(t)}$ where

$$F_{ib}^{1,(t)} = \langle \epsilon_i, (\tilde{\mu}_a - \mu_a^{(t)}) - (\tilde{\mu}_b - \mu_b^{(t)}) \rangle$$

is the error arising from the GMM part of the model and

$$F_{ib}^{2,(t)} = \lambda^{(t)} \langle E_i, W^{(t)}, (\tilde{\Pi}_a - \Pi_a^{(t)}) - (\tilde{\Pi}_b - \Pi_b^{(t)}) \rangle + \lambda^{(t)} \langle E_i, (W - W^{(t)}), \tilde{\Pi}_a - \tilde{\Pi}_b \rangle + (\lambda - \lambda^{(t)}) \langle E_i, W, \tilde{\Pi}_a - \tilde{\Pi}_b \rangle$$

is the error coming from the SBM part of the model. We have

$$F \leq 2 \underbrace{\max_{\{z^{(t)}: l(z, z^{(t)}) \leq \tau^{(0)}\}} \sum_{i=1}^n \max_{b \in [K] \setminus z_i} \frac{(F_{ib}^{1,(t)})^2}{\Delta(z_i, b)^2 l(z, z^{(t)})}}_{F_1^{(t)}} + 2 \underbrace{\max_{\{z^{(t)}: l(z, z^{(t)}) \leq \tau^{(0)}\}} \sum_{i=1}^n \max_{b \in [K] \setminus z_i} \frac{(F_{ib}^{2,(t)})^2}{\Delta(z_i, b)^2 l(z, z^{(t)})}}_{F_2^{(t)}}$$

and it is sufficient to individually control each term.

Control of F_1 . We follow the same steps as in Gao and Zhang (2019), the only difference is that we use a different definition for Δ . To begin with,

$$\begin{aligned} F_1^{(t)} &\leq \sum_{i=1}^n \sum_{b \in [K] \setminus z_i} \frac{\langle \epsilon_i, (\tilde{\mu}_{z_i} - \mu_{z_i}^{(t)}) - (\tilde{\mu}_b - \mu_b^{(t)}) \rangle^2}{\Delta(z_i, b)^2 l(z, z^{(t)})} \\ &\leq \sum_{b \in [K]} \sum_{a \in [K] \setminus b} \sum_{i \in \mathcal{C}_a} \frac{\langle \epsilon_i, (\tilde{\mu}_a - \mu_a^{(t)}) - (\tilde{\mu}_b - \mu_b^{(t)}) \rangle^2}{\Delta(a, b)^2 l(z, z^{(t)})} \\ &\leq \sum_{b \in [K]} \sum_{a \in [K] \setminus b} \left\| \sum_{i \in \mathcal{C}_a} \epsilon_i \epsilon_i^\top \right\| \frac{\|(\tilde{\mu}_a - \mu_a^{(t)}) - (\tilde{\mu}_b - \mu_b^{(t)})\|^2}{\Delta(a, b)^2 l(z, z^{(t)})}. \end{aligned}$$

We first need to control $\left\| \sum_{i \in \mathcal{C}_a} \epsilon_i \epsilon_i^\top \right\|$ which can be done using the following lemma.

Lemma 4. *Let $\epsilon_i \stackrel{i.i.d}{\sim} \mathcal{N}(0, I_d)$. With probability at least $1 - \exp(-0.5n)$, we have*

$$\left\| \sum_{i \in [n]} \epsilon_i \epsilon_i^\top \right\| \lesssim n + d.$$

Proof. See Lemma A.2 in Lu and Zhou (2016). □

Next, we need to control $\|\tilde{\mu}_a - \mu_a^{(t)}\|^2$ for all $a \in [K]$, this can be done with the following lemma.

Lemma 5. *Under the assumptions of Theorem 2, the following holds with probability at least $1 - n^{-\Omega(1)}$. If $z^{(t)}$ satisfies $l(z^{(t)}, z) \leq \tau^{(0)} = \frac{\epsilon n \Delta_{\min}^2}{K}$ then it implies*

1. $\max_{k \in [K]} \|\tilde{\mu}_k - \mu_k\| \lesssim \sqrt{\frac{K(d + \log n)}{n}},$
2. $\max_{k \in [K]} \|\mathbb{E}(X)^\top (W_{:k}^{(t)} - W_{:k})\| \lesssim \frac{K}{n \Delta_{\min}} l(z^{(t)}, z),$
3. $\max_{k \in [K]} \|(X - \mathbb{E}(X))^\top W_{:k}^{(t)}\| \lesssim \frac{K \sqrt{(d+n)l(z^{(t)}, z)}}{n \Delta_{\min}} + \frac{K \sqrt{K(d + \log n)l(z^{(t)}, z)}}{n \sqrt{n} \Delta_{\min}^2}$
4. $\|\tilde{\mu}_k - \mu_k^{(t)}\| \leq C_3 \frac{K \sqrt{(d+n)l(z^{(t)}, z)}}{n \Delta_{\min}}.$

Proof. Straightforward adaptation the proof of Lemma 4.1 in Gao and Zhang (2019). \square

By combining the different bounds, we can now conclude that with high probability,

$$\max_{\{z^{(t)}: l(z^{(t)}, z) \leq \tau^{(0)}\}} F_1^{(t)} \lesssim \frac{K^2(Kd/n + 1)}{\Delta_{min}^2} \left(1 + \frac{K(d/n + 1)}{\Delta_{min}^2} \right).$$

This quantity goes to zero when $\Delta_{min}^2/K^3 \rightarrow +\infty$.

Control of $F_2^{(t)}$. Here we can not directly apply the framework developed by Gao and Zhang (2019). Different changes are necessary and we need to deal with additional dependencies.

Let $b \in [K] \neq z_j$, we then have the bound

$$\begin{aligned} (F_{ib}^{2,(t)})^2 &\leq 3(\lambda^{(t)} \langle E_i: W^{(t)}, (\tilde{\Pi}_{a:} - \Pi_{a:}^{(t)}) - (\tilde{\Pi}_{b:} - \Pi_{b:}^{(t)}) \rangle)^2 \\ &\quad + 3(\lambda^{(t)} \langle E_i: (W - W^{(t)}), \tilde{\Pi}_{a:} - \tilde{\Pi}_{b:} \rangle)^2 \\ &\quad + 3(\lambda - \lambda^{(t)})^2 \langle E_i: W, \tilde{\Pi}_{a:} - \tilde{\Pi}_{b:} \rangle^2 \\ &= F_{21}^2 + F_{22}^2 + F_{33}^2. \end{aligned}$$

We drop the superscript (t) in the notation for the terms F_{21} , F_{22} and F_{23} for convenience, but clearly they depend on t as well. We will now bound each of the terms F_{2i} for $i = 1 \dots 3$ separately. Starting with F_{21} , first note that

$$|\langle E_i: W^{(t)}, (\tilde{\Pi}_{a:} - \Pi_{a:}^{(t)}) - (\tilde{\Pi}_{b:} - \Pi_{b:}^{(t)}) \rangle|^2 \leq 4 \|E_i: W^{(t)}\|^2 \max_k \|\tilde{\Pi}_{k:} - \Pi_{k:}^{(t)}\|^2.$$

With high probability, for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(0)}$ we have

$$\begin{aligned} \max_{k \in [K]} \|\tilde{\Pi}_{k:} - \Pi_{k:}^{(t)}\|^2 &\leq 2 \max_{k \in [K]} \|(W_{:k} - W_{:k}^{(t)})^\top A W\|^2 + 2 \max_{k \in [K]} \|W_{:k}^{(t)\top} A (W - W^{(t)})\|^2 \\ &\lesssim \left(\frac{K^2 \sqrt{p_{max} l(z^{(t)}, z)}}{n^{1.5} \Delta_{min}} \right)^2 && \text{(by Lemma 14)} \\ &\lesssim \frac{K^4 p_{max} l(z^{(t)}, z)^2}{n^3 \Delta_{min}^2} \end{aligned}$$

and since $\lambda^{(t)} \lesssim \lambda$ (by Lemma 16) it follows that

$$\begin{aligned} \sum_{i=1}^n \max_{b \in [K] \setminus z_i} \frac{F_{21}^2}{\Delta^2(z_i, b) l(z, z^{(t)})} &\lesssim \lambda^2 \sum_i \|E_i: W^{(t)}\|^2 \frac{K^4 p_{max} l(z^{(t)}, z)^2}{n^3 \Delta_{min}^2} \\ &\lesssim \lambda^2 \|E W^{(t)}\|_F^2 \frac{K^4 p_{max} l(z^{(t)}, z)}{n^3 \Delta_{min}^4} \\ &\lesssim \lambda^2 K \|E W^{(t)}\|^2 \frac{K^4 p_{max} l(z^{(t)}, z)}{n^3 \Delta_{min}^4} \\ &\lesssim \lambda^2 K^2 p_{max} \frac{K^4 p_{max} l(z^{(t)}, z)}{n^3 \Delta_{min}^4} && \text{(by a consequence of Lemma 14, fifth item)} \\ &\lesssim \frac{K^4 l(z^{(t)}, z)}{n \Delta_{min}^4} && \text{(since } \lambda \lesssim \frac{n}{K p_{max}} \text{)} \\ &\lesssim \frac{K^3}{\Delta_{min}^2} \rightarrow 0 \end{aligned}$$

where we used the fact $\frac{K l(z^{(t)}, z)}{n \Delta_{min}^2} \leq \epsilon$ for the last line. Indeed, $\frac{K l(z^{(t)}, z)}{n \Delta_{min}^2} \leq \frac{K \tau^{(0)}}{n \Delta_{min}^2} = \epsilon$.

Let us define $\Delta_2^2(a, b) := \|\Pi_a - \Pi_b\|^2$ for $a, b \in [K]$. Since

$$F_{22}^2 \lesssim \lambda^2 \|E_{i:}(W - W^{(t)})\|^2 \|\tilde{\Pi}_{z_i:} - \tilde{\Pi}_b\|^2 \lesssim \lambda^2 \|E_{i:}(W - W^{(t)})\|^2 \|\Pi_{z_i:} - \Pi_b\|^2$$

hence we have w.h.p. for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(0)}$

$$\begin{aligned} \sum_{i=1}^n \max_{b \in [K] \setminus z_i} \frac{F_{22}^2}{\Delta(z_i, b)^2 l(z, z^{(t)})} &\lesssim \lambda \sum_i \|E_{i:}(W - W^{(t)})\|^2 \frac{1}{l(z^{(t)}, z)} \max_{b \in [K] \setminus z_i} \frac{\lambda \|\Pi_{z_i:} - \Pi_b\|^2}{\Delta(z_i, b)^2} \\ &\lesssim \|E(W - W^{(t)})\|_F^2 \frac{\lambda}{l(z^{(t)}, z)} \quad (\text{because } \Delta^2(z_i, b) \geq \lambda \Delta_2^2(z_i, b)) \\ &\lesssim K \|E(W - W^{(t)})\|^2 \frac{\lambda}{l(z^{(t)}, z)} \\ &\lesssim \lambda K n p_{\max} \frac{K^3 l(z^{(t)}, z)}{n^3 \Delta_{\min}^4} \quad (\text{by Lemma 14}) \\ &\lesssim \frac{K^3}{\Delta_{\min}^2} \rightarrow 0. \end{aligned}$$

Using the same proof technique as in Lemma 1

$$(\langle E_{i:} W, \tilde{\Pi}_a - \tilde{\Pi}_b \rangle)^2 \lesssim K p_{\max} \Delta_2^2(a, b)$$

holds w.h.p. Since by Lemma 16 we have w.h.p. that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(0)}$

$$|\lambda^{(t)} - \lambda| \lesssim \lambda \frac{K^2 l(z^{(t)}, z)}{\sqrt{n p_{\max} n \Delta_{\min}}},$$

we obtain

$$\begin{aligned} \sum_{i=1}^n \max_{b \in [K] \setminus z_i} \frac{F_{23}^2}{\Delta(z_i, b)^2 l(z, z^{(t)})} &\lesssim \lambda^2 \left(\frac{K^2 l(z^{(t)}, z)}{\sqrt{n p_{\max} n \Delta_{\min}}} \right)^2 \sum_i \|E_{i:} W\|^2 \max_{b \in [K] \setminus z_i} \|\tilde{\Pi}_{z_i:} - \tilde{\Pi}_b\|^2 \frac{1}{\Delta^2(z_i, b) l(z^{(t)}, z)} \\ &\lesssim \lambda \frac{K^4 l(z^{(t)}, z)}{n^3 p_{\max} \Delta_{\min}^2} \|EW\|_F^2 \max_{b \in [K] \setminus z_i} \frac{\lambda \|\Pi_{z_i:} - \Pi_b\|^2}{\Delta^2(z_i, b)} \\ &\lesssim \frac{n}{K p_{\max}} \frac{K^4 l(z^{(t)}, z)}{n^3 p_{\max} \Delta_{\min}^2} K p_{\max} \quad (\text{by Lemma 9}) \\ &\lesssim \frac{K^4 l(z^{(t)}, z)}{n^2 p_{\max} \Delta_{\min}^2} \\ &\lesssim \frac{K^3}{n p_{\max}} \\ &\lesssim \frac{K^3}{\Delta_{\min}^2} \rightarrow 0. \end{aligned}$$

Consequently, we have established that Condition B holds for all $\delta = o(1)$ such that $\delta^2 = \omega(K^3 / \Delta_{\min}^2)$. \square

C.3 Error term $G_{ib}^{(t)}$

In this section we are going to show that the G - error term satisfied condition C.

Lemma 6. *Under the assumptions of Theorem 4 (that are also satisfied by Theorem 2) we have w.h.p. for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$*

$$\max_{i \in [n]} \max_{b \in [K] \setminus z_i} \frac{|G_{ib}^{(t)}|}{\Delta(z_i, b)^2} \leq \frac{\delta^{(t)}}{8}.$$

Proof. As for $F_{ib}^{(t)}$ we can split $G_{ib}^{(t)} = G_{ib}^{1,(t)} + G_{ib}^{2,(t)}$ where

$$\begin{aligned} G_{ib}^{1,(t)} &= \|\mu_a - \mu_a^{(t)}\|^2 - \|\mu_a - \tilde{\mu}_a\|^2 - (\|\mu_a - \mu_b^{(t)}\|^2 - \|\mu_a - \tilde{\mu}_b\|^2) \\ G_{ib}^{2,(t)} &= \lambda^{(t)}(\|P_{i:}W^{(t)} - \Pi_{a:}^{(t)}\|^2 - \|P_{i:}W^{(t)} - W_{a:}AW^{(t)}\|^2) - \lambda^{(t)}(\|P_{i:}W^{(t)} - \Pi_{b:}^{(t)}\|^2 - \|P_{i:}W^{(t)} - W_{b:}AW^{(t)}\|^2). \end{aligned}$$

By the proof of Lemma 4.1 in Gao and Zhang (2019) (last inequality of page 46, equations (115) and (118)), we have w.h.p. for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$,

$$\begin{aligned} \frac{|G_{ib}^{1,(t)}|}{\Delta^2(a, b)} &\lesssim \left(\frac{Kl(z^{(t)}, z)}{n\Delta_{min}} + K\sqrt{\frac{Kl(z^{(t)}, z)}{n\Delta_{min}}} \right)^2 \Delta_{min}^{-2} \\ &\quad + \left(\frac{Kl(z^{(t)}, z)}{n\Delta_{min}} + K\sqrt{\frac{Kl(z^{(t)}, z)}{n\Delta_{min}}} \right) \frac{Kl(z^{(t)}, z)}{n\Delta_{min}} \Delta_{min}^{-2} + \left(\frac{Kl(z^{(t)}, z)}{n\Delta_{min}} + K\sqrt{\frac{Kl(z^{(t)}, z)}{n\Delta_{min}}} \right) \Delta_{min}^{-1} \\ &\lesssim \frac{Kl(z^{(t)}, z)^2}{n^2\Delta_{min}^4} + K\frac{l(z^{(t)}, z)}{n\Delta_{min}^2} \\ &\lesssim K\frac{l(z^{(t)}, z)}{n\Delta_{min}^2} \quad (\text{since } K\frac{l(z^{(t)}, z)}{n\Delta_{min}^2} < 1 \text{ and } \frac{Kl(z^{(t)}, z)^2}{n^2\Delta_{min}^4} < \frac{1}{K}) \\ &\lesssim \frac{K\tau^{(t)}}{n\Delta_{min}^2} \\ &\lesssim \max\left(\frac{7}{8}\frac{K\tau^{(t-1)}}{n\Delta_{min}^2}, \frac{K\tau}{n\Delta_{min}^2}\right) \quad (\text{by definition of } \tau^{(t)}) \\ &\lesssim \max\left(\frac{7}{8}\left(\frac{8}{7}\epsilon\right)\delta^{(t)}, \epsilon\delta\right) \quad (\text{using } \tau = \tau^{(0)}\delta \text{ and also the definition of } \delta^{(t)}) \\ &\lesssim \epsilon\delta^{(t)}. \quad (\text{since } \delta \leq \delta^{(t)}) \end{aligned}$$

Now by choosing ϵ to be a suitably small constant (< 1), we obtain

$$\frac{|G_{ib}^{1,(t)}|}{\Delta^2(a, b)} \leq \frac{\delta^{(t)}}{16}.$$

To bound $G_{ib}^{2,(t)}$ we will adapt the method developed in Han et al. (2020). We have by direct calculation

$$\begin{aligned} \frac{G_{ib}^{2,(t)}}{\lambda^{(t)}} &= (\|\Pi_{a:}^{(t)} - W_{a:}^\top AW^{(t)}\|^2 - \|\Pi_{b:}^{(t)} - W_{b:}^\top AW^{(t)}\|^2) + \langle P_{i:}W^{(t)} - W_{a:}AW^{(t)}, W_{a:}^\top AW^{(t)} - \Pi_{a:}^{(t)} \rangle \\ &\quad - \langle P_{i:}W^{(t)} - W_{b:}AW^{(t)}, W_{b:}^\top AW^{(t)} - \Pi_{b:}^{(t)} \rangle \\ &\leq \left| \|\Pi_{a:}^{(t)} - W_{a:}^\top AW^{(t)}\|^2 - \|\Pi_{b:}^{(t)} - W_{b:}^\top AW^{(t)}\|^2 \right| + 4 \max_{k \in [K]} \left| \langle W_{a:}^\top EW^{(t)}, (W_{:b} - W_{:b}^{(t)})^\top AW^{(t)} \rangle \right| \\ &\quad + 2 \left| \langle (\Pi_{a:} - \Pi_{b:})Z^\top W^{(t)}, (W_{:b} - W_{:b}^{(t)})^\top AW^{(t)} \rangle \right| \\ &= G_{21} + G_{22} + G_{23}. \end{aligned}$$

We drop the superscript (t) in the notation for the terms G_{21} , G_{22} and G_{23} for convenience, but clearly they depend on t as well. First observe that w.h.p, it holds for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$ that

$$G_{21} \leq \max_{k \in [K]} \|\Pi_{a:}^{(t)} - W_{a:}^\top AW^{(t)}\|^2 = \max_{k \in [K]} \|(W_{a:}^{(t)} - W_{a:})^\top AW^{(t)}\|^2 \lesssim \frac{K^3 p_{max} l(z^{(t)}, z)^2}{n^3 \Delta_{min}^2}$$

where we used Lemma 14 for the last inequality. This implies by Lemma 15 that

$$\max_{b \in [K] \setminus z_i} \frac{\lambda^{(t)} G_{21}}{\Delta^2(z_i, b)} \lesssim \frac{K^2 l(z^{(t)}, z)^2}{n^2 \Delta_{min}^4} \leq \frac{K^2 (\tau^{(0)} \delta^{(t)})^2}{n^2 \Delta_{min}^4}$$

which implies $\max_{b \in [K] \setminus z_i} \frac{\lambda^{(t)} G_{21}}{\Delta^2(z_i, b)} \leq (\frac{\delta^{(t)}}{16})^2$ using the same argument used earlier (for suitably small constant $\epsilon < 1$). Next, in order to bound G_{22} , note that w.h.p, it holds for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$ that

$$\begin{aligned} G_{22} &\leq 4 \max_{a \in [K]} \|W_{:a}^\top E W^{(t)}\| \max_{a \in [K]} \|(W_{:b} - W_{:b}^{(t)})^\top A W^{(t)}\| \\ &\lesssim \frac{K \sqrt{p_{max}}}{\sqrt{n}} \frac{K^{1.5} \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}} \quad (\text{by Lemma 14}) \\ &\lesssim K^{2.5} \frac{p_{max}}{n} \frac{l(z^{(t)}, z)}{n \Delta_{min}} \end{aligned}$$

which in turn implies

$$\begin{aligned} \max_{b \in [K] \setminus z_i} \frac{\lambda^{(t)} G_{22}}{\Delta(z_i, b)^2} &\lesssim \frac{\sqrt{K}}{\Delta_{min}} \frac{K l(z^{(t)}, z)}{n \Delta_{min}^2} \quad (\text{since } \lambda^{(t)} \lesssim n / (K p_{max})) \\ &= o(\delta) \end{aligned}$$

as $\sqrt{K} / \Delta_{min} \rightarrow 0$ and $K \frac{l(z^{(t)}, z)}{n \Delta_{min}^2} < 1$.

Finally, in order to bound G_{23} , note that w.h.p, it holds for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$,

$$\begin{aligned} G_{23} &\lesssim \|\Pi_{a \cdot} - \Pi_{b \cdot}\| Z^\top W^{(t)} \max_{b \in [K]} \|(W_{:b} - W_{:b}^{(t)})^\top A W^{(t)}\| \\ &\lesssim \Delta_2(a, b) \frac{K^{1.5} \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}} \end{aligned}$$

which implies

$$\begin{aligned} \max_{b \in [K] \setminus z_i} \frac{\lambda^{(t)} G_{23}}{\Delta(z_i, b)^2} &\lesssim \lambda \frac{\Delta_2(z_i, b)}{\Delta(z_i, b)} \frac{K^{1.5} \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}^2} \\ &\lesssim \sqrt{\lambda} \frac{\sqrt{K p_{max}}}{\sqrt{n}} \frac{K l(z^{(t)}, z)}{n \Delta_{min}^2} \\ &\lesssim \frac{K l(z^{(t)}, z)}{n \Delta_{min}^2}. \quad (\text{since } \lambda \lesssim \frac{n}{K p_{max}}) \end{aligned}$$

For a suitably constant $\epsilon < 1$, this then implies

$$\max_{b \in [K] \setminus z_i} \frac{\lambda^{(t)} G_{23}}{\Delta(z_i, b)^2} \leq \frac{\delta^{(t)}}{16}.$$

□

C.4 Error term $H_{ib}^{(t)}$

In this section we are going to show that the H - error term satisfied condition C.

Lemma 7. *Under the assumptions of Theorem 4 (that are also satisfied by Theorem 2) we have w.h.p. that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$,*

$$\max_{i \in [n]} \max_{b \in [K] \setminus z_i} \frac{|H_{ib}^{(t)}|}{\Delta(z_i, b)^2} \leq \frac{\delta^{(t)}}{8}.$$

Proof. As before, we can split $H_{ib}^{(t)} = H_{ib}^{1,(t)} + H_{ib}^{2,(t)}$ where

$$2H_{ib}^{1,(t)} = \|\mu_a - \tilde{\mu}_a\|^2 - \|\mu_a - \tilde{\mu}_b\|^2 + \|\mu_a - \mu_b\|^2$$

$$2H_{ib}^{2,(t)} = \lambda^{(t)} (\|P_i W^{(t)} - W_{a \cdot}^\top A W^{(t)}\|^2 - \|P_i W^{(t)} - W_{b \cdot}^\top A W^{(t)}\|^2 + \|\Pi_{a \cdot} - \Pi_{b \cdot}\|^2) + (\lambda - \lambda^{(t)}) \|\Pi_{a \cdot} - \Pi_{b \cdot}\|^2.$$

By an immediate adaptation of Lemma 4.1 in Gao and Zhang (2019) it holds w.h.p. that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$,

$$\frac{|H_{ib}^{1,(t)}|}{\Delta(z_i, b)^2} \lesssim \frac{K(d + \log n)}{n\Delta_{min}^2} + \sqrt{\frac{K(d + \log n)}{n\Delta_{min}^2}} \rightarrow 0$$

as long as $K/\Delta_{min}^2 \rightarrow 0$.

It remains to uniformly control $H_{ib}^{2,(t)}$, let us split it² as $H_{ib}^{2,(t)} = \lambda^{(t)}H_1 + H_2$. First note that by Lemma 16 it holds w.h.p. that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$,

$$H_2 := (\lambda - \lambda^{(t)})\|\Pi_a - \Pi_b\|^2 \lesssim \lambda \frac{Kl(z^{(t)}, z)}{n\Delta_{min}^2} \Delta_2^2(a, b)$$

which implies

$$\frac{|H_2|}{\Delta(z_i, b)^2} \lesssim \frac{Kl(z^{(t)}, z)}{n\Delta_{min}^2}.$$

Then, we obtain $\frac{|H_2|}{\Delta(z_i, b)^2} \leq \frac{\delta^{(t)}}{16}$ for a small enough constant $\epsilon < 1$.

Now observe that

$$\begin{aligned} H_1 &:= \|P_i W^{(t)} - W_a^\top A W^{(t)}\|^2 - \|P_i W^{(t)} - W_b^\top A W^{(t)}\|^2 + \|\Pi_a - \Pi_b\|^2 \\ &= \|W_a^\top E W^{(t)}\|^2 + (\|\Pi_a - \Pi_b\|^2 - \|P_i W^{(t)} - W_b^\top P W^{(t)}\|^2) \\ &\quad - (\|P_i W^{(t)} - W_b^\top A W^{(t)}\|^2 - \|P_i W^{(t)} - W_b^\top P W^{(t)}\|^2) \\ &= (\|\Pi_a - \Pi_b\|^2 - \|P_i W^{(t)} - W_b^\top P W^{(t)}\|^2) + (\|W_a^\top E W^{(t)}\|^2 - \|W_b^\top E W^{(t)}\|^2) \\ &\quad + 2\langle P_i W^{(t)} - W_b^\top P W^{(t)}, W_b^\top E W^{(t)} \rangle \\ &= H_{11}^{(t)} + H_{12}^{(t)} + H_{13}^{(t)}. \end{aligned}$$

By writing

$$P_i W^{(t)} - W_b^\top P W^{(t)} = (\Pi_a - \Pi_b) Z^\top W^{(t)},$$

we obtain w.h.p. that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$,

$$|H_{13}^{(t)}| \lesssim \|P_i W^{(t)} - W_b^\top P W^{(t)}\| \|W_b^\top E W^{(t)}\| \lesssim \|\Pi_a - \Pi_b\| \frac{K\sqrt{p_{max}}}{\sqrt{n}} \lesssim \|\Pi_a - \Pi_b\|^2 \frac{K}{\sqrt{np_{max}}}.$$

In particular,

$$\frac{\lambda^{(t)}|H_{13}^{(t)}|}{\Delta^2(z_i, b)} \lesssim \frac{\lambda \Delta_2^2(z_i, b) K}{\Delta^2(z_i, b) \sqrt{np_{max}}} \lesssim \frac{K}{\sqrt{np_{max}}} \rightarrow 0.$$

Next observe that w.h.p., it holds for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$ that

$$\left| \|W_a^\top E W^{(t)}\|^2 - \|W_b^\top E W^{(t)}\|^2 \right| \leq \max_{k \in [K]} \|W_k^\top E W^{(t)}\|^2 \lesssim \frac{K^2 p_{max}}{n}$$

where the last inequality uses Lemma 14. This implies

$$\frac{\lambda^{(t)}|H_{12}^{(t)}|}{\Delta^2(z_i, b)} \lesssim \frac{K}{\Delta_{min}^2} \rightarrow 0.$$

Finally, it remains to bound $|H_{11}^{(t)}|$. To begin with,

$$|H_{11}^{(t)}| := \left| \|\Pi_a - \Pi_b\|^2 - \|P_i W^{(t)} - W_b^\top P W^{(t)}\|^2 \right| = \left| \|\Pi_a - \Pi_b\|^2 - \|(\Pi_a - \Pi_b) Z^\top W^{(t)}\|^2 \right|.$$

²We drop the superscript (t) in the notation for H_1, H_2 for convenience, but clearly they both depend on t as well.

Using the fact

$$\left| \|\Pi_{a:} - \Pi_{b:}\|^2 - \|(\Pi_{a:} - \Pi_{b:})Z^\top W^{(t)}\|^2 \right| \leq \left(\|Z^\top W^{(t)} - I\|^2 + 2 \|Z^\top W^{(t)} - I\| \right) \|\Pi_{a:} - \Pi_{b:}\|^2,$$

we obtain by the proof of part 1 of Lemma 14 that w.h.p., it holds for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(t)}$

$$|H_{11}^{(t)}| \lesssim \|\Pi_{a:} - \Pi_{b:}\|^2 \frac{Kl(z^{(t)}, z)}{n\Delta_{min}^2}$$

which implies

$$\frac{\lambda^{(t)}|H_{11}^{(t)}|}{\Delta^2(z_i, b)} \lesssim \frac{Kl(z^{(t)}, z)}{n\Delta_{min}^2}.$$

Then as before, for a suitably small constant $\epsilon < 1$, this implies

$$\frac{\lambda^{(t)}|H_{11}^{(t)}|}{\Delta^2(z_i, b)} \leq \frac{\delta^{(t)}}{16}.$$

By summing all these inequalities we see that $G_{ib}^{(t)}$ and $H_{ib}^{(t)}$ satisfy Condition C. \square

C.5 Conclusion

By Lemma 3, 6 and 7 the Conditions B and C are satisfied. In order to apply Theorem 1, we also need to show that Condition A is satisfied. To this end, let us define the events

$$\Omega(\delta^{(t)}) := \{C_i(a, b) \leq -\left(\frac{1 - \delta^{(t)}}{2}\right) \Delta^2(a, b)\}, \quad t \geq 1,$$

where we recall that

$$C_i(a, b) = \langle \epsilon_i, \tilde{\mu}_a - \tilde{\mu}_b \rangle + \lambda \langle E_i; W, \tilde{\Pi}_a - \tilde{\Pi}_b \rangle.$$

Note that by definition of $\delta^{(t)}$, we have for all $t \geq 1$

$$\Omega(\delta^{(t)}) \subseteq \Omega(\delta^{(1)}) \implies \mathbf{1}_{\Omega(\delta^{(t)})} \leq \mathbf{1}_{\Omega(\delta^{(1)})} \implies \xi(\delta^{(t)}) \leq \xi(\delta^{(1)}). \quad (\text{C.1})$$

Hence it suffices to bound $\xi(\delta^{(1)})$. To achieve this, it is crucial to bound $\mathbb{P}(\Omega(\delta^{(1)}))$ since the bound on $\xi(\delta^{(1)})$ then follows via an easy adaptation of Lemma 1.

We can bound $\mathbb{P}(\Omega(\delta^{(1)}))$ by an immediate adaptation of Lemma 10 – we just need to replace $\Delta^2/4$ by $(1 - \delta^{(1)})\Delta^2/4$ in the last step of the lemma, leading to

$$\mathbb{P}(\Omega(\delta^{(1)})) \leq \exp(-(1 - \delta^{(1)} + o(1))\tilde{\Delta}^2).$$

Then as mentioned earlier, an easy adaptation of Lemma 1 along with (C.1) implies that w.h.p., it holds for all $t \geq 1$ that

$$\xi(\delta^{(t)}) \leq n \exp(-(1 - \delta^{(1)} + o(1))\tilde{\Delta}^2).$$

But we know that

$$n \exp(-(1 - \delta^{(1)} + o(1))\tilde{\Delta}^2) \leq \frac{3}{4}\tau = \frac{3}{4}\tau^{(0)}\delta$$

for n large enough, by a suitable choice of $\delta = o(1)$, and the fact that $\tilde{\Delta}^2 \asymp \log n/K \rightarrow \infty$. Hence the assumptions of Theorem 1 are satisfied. Moreover, for all $t \gtrsim \log(1/\delta)$, Corollary 1 yields the bound

$$l(z^{(t)}, z) \lesssim \xi(\delta) + \tau^{(0)}(1/8)^{t - \Theta(\log(1/\delta))} \lesssim ne^{-(1+o(1))\tilde{\Delta}^2} + \tau^{(0)}(1/8)^{t - \Theta(\log(1/\delta))}.$$

Since $\tau^{(0)} \lesssim n \log n/K$ and δ can be chosen such that $\log(1/\delta) \lesssim \log n$, we obtain that for $t \gtrsim \log n$

$$l(z^{(t)}, z) \leq ne^{-(1+o(1))\tilde{\Delta}^2}.$$

D Proof of Theorem 3

Proof. The proof follows the same lines as in (Lu and Zhou, 2016, Theorem 3.3), only the last part needs to be changed. For the sake of completeness, we reproduce the arguments below. Let us denote

$$h(z', z'') = \sum_{i \in [n]} \mathbf{1}_{\{z'(i) \neq z''(i)\}} \quad (\text{D.1})$$

to be the unnormalized Hamming distance between $z', z'' \in [K]^n$. Without loss of generality we can assume that

$$\min_{k, k'} \|\mu_k - \mu_{k'}\| = \|\mu_1 - \mu_2\|.$$

For each $k \in [K]$, let T_k a subset of \mathcal{C}_k with cardinality $\frac{3n}{4K}$. Define $T = \cup_{k=1}^K T_k$ and

$$\mathcal{Z} = \{\hat{z} : \hat{z}_i = z_i \text{ for all } i \in T\}.$$

For all $\hat{z} \neq \tilde{z} \in \mathcal{Z}$ we have

$$\frac{h(\hat{z}, \tilde{z})}{n} \leq \frac{1}{4}$$

and for all permutations $\sigma \in \mathfrak{S}_K, \sigma \neq Id$ (where Id denotes the identity permutation) we have

$$\frac{h(\sigma(\hat{z}), \tilde{z})}{n} \geq \frac{1}{2}.$$

Thus $r(\hat{z}, \tilde{z}) = \frac{h(\hat{z}, \tilde{z})}{n}$. Then following the same arguments as in the proof of Theorem 2 in Gao et al. (2016) we can obtain

$$\inf_{\hat{z}} \sup_{\theta \in \Theta} \mathbb{E}(r(\hat{z}, z)) \geq \frac{1}{6|T^c|} \sum_{i \in T^c} \frac{1}{2K^2} \inf_{\hat{z}_i} (\mathbb{P}_1(\hat{z}_i = 2) + \mathbb{P}_2(\hat{z}_i = 1)) \quad (\text{D.2})$$

where \mathbb{P}_k denotes the probability distribution of the data when $z_i = k$. By the Neyman Pearson Lemma, the infimum of the right hand side of (D.2) is achieved by the likelihood ratio test. From (Zhang and Zhou, 2016, Section 3.1), the log-likelihood of the SBM part can be rewritten as

$$\log \left(\frac{p(1-q)}{q(1-p)} \right) \sum_{i < j} A_{ij} \mathbf{1}_{\{z_i = z_j\}} + f(A)$$

where $f(A)$ doesn't depend on z . Consequently,

$$\begin{aligned} & \frac{1}{2} \inf_{\hat{z}_i} (\mathbb{P}_1(\hat{z}_i = 2) + \mathbb{P}_2(\hat{z}_i = 1)) \\ &= \mathbb{P} \left(-0.5 \|\epsilon_i\|^2 + \log \left(\frac{p(1-q)}{q(1-p)} \right) \sum_{j \in \mathcal{C}_1} A_{ij} \leq -0.5 \|\mu_1 + \epsilon_i - \mu_2\|^2 + \log \left(\frac{p(1-q)}{q(1-p)} \right) \sum_{j \in \mathcal{C}_2} A_{ij} \right) \quad (\text{D.3}) \end{aligned}$$

Let us denote $Z_i = \log \left(\frac{p(1-q)}{q(1-p)} \right) (\sum_{j \in \mathcal{C}_2} A_{ij} - \sum_{j \in \mathcal{C}_1} A_{ij})$, this is a random variable independent of ϵ_i . So we get

$$\begin{aligned} (\text{D.3}) &= \mathbb{P}(0.5 \|\mu_1 - \mu_2\|^2 - Z_i \leq \langle \epsilon_i, \mu_1 - \mu_2 \rangle) \\ &\geq \mathbb{P}(0.5 \|\mu_1 - \mu_2\|^2 - Z_i \leq \langle \epsilon_i, \mu_1 - \mu_2 \rangle \mid Z_i > 0) \mathbb{P}(Z_i > 0) \\ &\geq \mathbb{P}(\|\mu_1 - \mu_2\|^2 \leq 2 \langle \epsilon_i, \mu_1 - \mu_2 \rangle) \mathbb{P}(Z > 0) \\ &\geq \exp \left(-\frac{\Delta_1^2}{8} \right) \exp \left(-n \frac{(1 + o(1))(\sqrt{p} - \sqrt{q})^2}{K} \right) \\ &\geq \exp(-(1 + o(1))\tilde{\Delta}^2). \end{aligned}$$

Here we used for the penultimate inequality a result from the proof of (Lu and Zhou, 2016, Theorem 3.3) and also use (Zhang and Zhou, 2016, Lemma 5.2). \square

E Technical Lemmas

In this section we provide some useful inequalities which are used frequently in the proofs of our main results.

E.1 General concentration inequalities

Lemma 8 (Chernoff simplified bound). *Let $X_1, \dots, X_n \stackrel{ind.}{\sim} \mathcal{B}(p)$. Then*

$$\mathbb{P} \left(\left| \frac{1}{n} \sum_{i \in [n]} X_i - p \right| \geq t \right) \leq \exp(-2nt^2).$$

Lemma 9. *Assume that $A \sim SBM(Z, \Pi)$. Let $E = A - \mathbb{E}(A)$. Then with probability at least $1 - n^{-\Omega(1)}$ the following holds.*

1. $\|E\| \leq \sqrt{np_{max}}$,
2. $\|EW\|_F^2 \lesssim K^2 p_{max}$.

Proof. The first inequality is a classical result used for SBM in the relatively sparse regime $p_{max} = \omega(\log n)$. It can be obtained as a consequence of Remark 3.13 in Bandeira and van Handel (2016). The second inequality follows from

$$\|EW\|_F^2 \leq K \|EW\|^2 \leq K \|E\|^2 \|W\|^2 \lesssim K^2 p_{max}.$$

□

E.2 Concentration rate for the ideal oracle error under CSSBM

Lemma 10. *Recall that*

$$\Omega_1 = \left\{ \langle \epsilon_i, \mu_{z_i} - \mu_b \rangle + \lambda \langle E_i, W, \Pi_{z_i} - \Pi_b \rangle \leq \frac{-(1 - \delta - \bar{\delta}) \Delta^2(z_i, b)}{2} \right\}$$

and suppose that $\delta, \bar{\delta} = o(1)$. Then under the assumptions of Theorem 2, we have

$$\mathbb{P}(\Omega_1) \leq \exp(-(1 + o(1)) \tilde{\Delta}^2)$$

where

$$\tilde{\Delta}^2 = \frac{1}{8} \min_{k, k'} \|\mu_k - \mu_{k'}\|^2 + \frac{\log n}{K} (\sqrt{p'} - \sqrt{q'})^2.$$

Proof. We are going to bound the m.g.f of $Z = \langle \epsilon_i, \mu_{z_i} - \mu_b \rangle + \lambda \langle E_i, W, \Pi_{z_i} - \Pi_b \rangle$ and use Chernoff method. We have for all $t < 0$

$$\begin{aligned} \log \mathbb{E} e^{tZ} &\leq \log \mathbb{E} e^{t \langle \epsilon_i, \mu_{z_i} - \mu_b \rangle} + \log \mathbb{E} e^{t \lambda \langle E_i, W, \Pi_{z_i} - \Pi_b \rangle} && \text{(by independence)} \\ &\leq \|\mu_{z_i} - \mu_b\|^2 \frac{t^2}{2} + \frac{n}{K} \log(pe^{t \lambda (p-q)K/n} + 1 - p)(qe^{-t \lambda (p-q)K/n} + 1 - q) \\ &\quad - t \lambda (p - q)^2. \end{aligned}$$

By choosing $t = -1/2$ we get

$$e^{t \lambda (p-q)K/n} = \sqrt{\frac{q(1-p)}{p(1-q)}}$$

and thus

$$\log(pe^{t \lambda (p-q)K/n} + 1 - p)(qe^{-t \lambda (p-q)K/n} + 1 - q) = \log(pq + (1-p)(1-q) + 2\sqrt{pq}\sqrt{(1-p)(1-q)}).$$

This last quantity is equal to $-(1 + o(1))(\sqrt{p} - \sqrt{q})^2$. We can now conclude by remarking that

$$\mathbb{P}(\Omega_1) \leq \mathbb{P}\left(-\frac{1}{2}\langle \epsilon_i, \mu_{z_i} - \mu_b \rangle - \frac{1}{2}\lambda\langle E_i; W, \Pi_{z_i} - \Pi_b \rangle \geq (1 + o(1))\frac{\Delta_{min}^2}{4}\right)$$

hence

$$\begin{aligned} \mathbb{P}(\Omega_1) &\leq \mathbb{E}e^{-\frac{Z}{2} - \frac{\Delta_{min}^2}{4}} \\ &\leq \exp\left(\frac{\|\mu_{z_i} - \mu_b\|^2}{8} - \frac{n}{K}(1 + o(1))(\sqrt{p} - \sqrt{q})^2 + \frac{\lambda}{2}(p - q)^2 - (1 + o(1))\frac{\Delta_{min}^2}{4}\right) \\ &\leq \exp(-(1 + o(1))\tilde{\Delta}^2), \end{aligned}$$

since $\Delta_{min}^2 = \|\mu_{z_i} - \mu_b\|^2 + 2\lambda(p - q)^2$. □

E.3 Concentration rate for the ideal oracle error under the general setting

In the general setting it is more difficult to derive a sharp concentration inequality for the oracle error. Here we use gaussian approximation, but it leads to a slightly sub-optimal convergence rate.

Lemma 11. *Recall the definition of Ω_1 from the previous lemma. Under the assumptions of Theorem 4 we have*

$$\mathbb{P}(\Omega_1) \leq \exp\left(-\frac{1}{8}\Delta_{min}^2\right).$$

Proof. First observe that

$$\begin{aligned} t\lambda\langle E_i; W, \Pi_{z_i} - \Pi_b \rangle &= t\lambda \sum_{k \in [K]} (\Pi_{z_i k} - \Pi_{bk}) \frac{\sum_{j \in \mathcal{C}_k} E_{ij}}{n_k} \\ &= \sum_{k \in [K]} t\lambda (\Pi_{z_i k} - \Pi_{bk}) \frac{\sum_{j \in \mathcal{C}_k} A_{ij} - \Pi_{z_i k}}{n_k}. \end{aligned}$$

The sum over k involves independent random variables so in order to bound the *m.g.f.* of $\langle E_i; W, \Pi_{z_i} - \Pi_b \rangle$ it is sufficient to control the *m.g.f.* of $\sum_{j \in \mathcal{C}_k} A_{ij} - \Pi_{z_i k}$ for each k . Setting $t' = \lambda t \frac{|\Pi_{z_i k} - \Pi_{bk}|}{n_k}$, we have

$$\begin{aligned} \log \mathbb{E}(e^{t' \sum_{j \in \mathcal{C}_k} (A_{ij} - \Pi_{z_i k})}) &= \log(\Pi_{z_i k} e^{t'} + 1 - \Pi_{z_i k}) - n_k t' \Pi_{z_i k} \\ &\leq n_k \Pi_{z_i k} (e^{t'} - t' - 1) \\ &\leq n_k \Pi_{z_i k} \frac{e^{(t')^2}}{2} \quad (\text{by Taylor-Lagrange inequality}) \\ &\leq 1.5 n_k p_{max} \left(\lambda t \frac{|\Pi_{z_i k} - \Pi_{bk}|}{n_k}\right)^2 \\ &\leq 1.5 \lambda |\Pi_{z_i k} - \Pi_{bk}|^2 t^2. \end{aligned}$$

For the second inequality we used the fact that for $0 < x < 1$, $\log(1 - x) \leq -x$.

Consequently,

$$\log \mathbb{E}e^{tZ} \leq \|\mu_{z_i} - \mu_b\|^2 \frac{t^2}{2} + 1.5 \lambda \|\Pi_{z_i} - \Pi_b\|^2 t^2$$

and

$$\mathbb{P}(\Omega_1) \leq e^{\|\mu_{z_i} - \mu_b\|^2 \frac{t^2}{2} + 1.5 \lambda \|\Pi_{z_i} - \Pi_b\|^2 t^2 - \frac{\Delta^2(z_i, b)}{4}}.$$

For $t = 1/2$ we then obtain

$$\mathbb{P}(\Omega_1) \leq e^{-\frac{\|\mu_{z_i} - \mu_b\|^2}{8} - \frac{\lambda}{8} \|\Pi_{z_i} - \Pi_b\|^2} \leq e^{-\frac{1}{8}\Delta_{min}^2}.$$

□

E.4 Useful inequalities to control the error terms

Recall the Hamming distance h defined in (D.1).

Lemma 12. *For all $z, z' \in [K]^n$ we have*

$$h(z, z') \leq \frac{l(z, z')}{\Delta_{min}^2}.$$

Proof.

$$\sum_{i \in [n]} \mathbf{1}_{z_i \neq z'_i} \leq \sum_{i \in [n]} \frac{\Delta(z_i, z'_i)^2}{\Delta_{min}^2} \mathbf{1}_{z_i \neq z'_i} = \frac{l(z, z')}{\Delta_{min}^2}.$$

□

Lemma 13. *Assume that for some $\alpha > 1$*

$$\frac{n}{\alpha K} \leq n_k \leq \frac{\alpha n}{K}.$$

If $l(z, z^{(t)}) \leq n\Delta_{min}^2/(2\alpha K)$ then for all $k \in [K]$

$$\frac{n}{2\alpha K} \leq n_k^{(t)} \leq \frac{2\alpha n}{K}.$$

Proof. Since for all $k \in [K]$ we have $n/(\alpha K) \leq n_k \leq \alpha n/K$,

$$\begin{aligned} \sum_{i \in \mathcal{C}_k^{(t)}} 1 &\geq \sum_{i \in \mathcal{C}_k \cap \mathcal{C}_k^{(t)}} 1 \geq \sum_{i \in \mathcal{C}_k} 1 - \sum_{i \in [n]} \mathbf{1}_{z_i \neq z_i^{(t)}} \\ &\geq \frac{n}{\alpha K} - h(z, z^{(t)}) \stackrel{\text{Lemma 12}}{\geq} \alpha \frac{n}{K} - \frac{l(z, z^{(t)})}{\Delta_{min}^2} \\ &\geq \frac{\alpha n}{2K} \end{aligned}$$

by assumption. The other inequality is proved in a similar way. □

Lemma 14. *Assume that $A \sim SBM(Z, \Pi)$ with equal size communities and suppose that the conditions of Theorem 4 are satisfied³. Then with probability at least $1 - n^{-\Omega(1)}$ the following holds for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(0)}$.*

1. $\max_{k \in [K]} \|W_{:k}^{(t)} - W_{:k}\| \lesssim \frac{K^{1.5}}{n^{1.5}\Delta_{min}^2} l(z^{(t)}, z),$
2. $\max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})^\top A W\| \lesssim \frac{K^{1.5}\sqrt{p_{max}}}{n^{1.5}\Delta_{min}} l(z, z^{(t)}),$
3. $\max_{k \in [K]} \|W_{:k}^{(t)\top} A(W - W^{(t)})\| \lesssim \frac{K^2\sqrt{p_{max}}l(z^{(t)}, z)}{n^{1.5}\Delta_{min}},$
4. $\max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})^\top A W^{(t)}\| \lesssim \frac{K^{1.5}\sqrt{p_{max}}l(z^{(t)}, z)}{n^{1.5}\Delta_{min}},$
5. $\|Z^\top W^{(t)}\| \lesssim 1.$

Proof. This is a rather straightforward adaptation of Lemma 4 in Han et al. (2020), but for completeness we include a proof adapted to our setting with our notations.

³These assumptions are clearly satisfied by Theorem 2 as well.

Proof of 1. First observe that Z is rank K and $\lambda_K(Z) = \sqrt{n_{min}}$ so that

$$\|W_{:k}^{(t)} - W_{:k}\| \leq n_{min}^{-1/2} \|I - Z^\top W^{(t)}\|.$$

For any $k \in [K]$, denote $\delta_k = 1 - (Z^\top W^{(t)})_{kk}$. Since for all $k, k' \in [K]$

$$(Z^\top W^{(t)})_{kk'} = \frac{\sum_{i \in \mathcal{C}_k} \mathbf{1}_{z_i^{(t)} = k'}}{n_{k'}^{(t)}},$$

we have

$$0 \leq \delta_k \leq 1, \quad \sum_{k' \in [K] \setminus k} (Z^\top W^{(t)})_{k'k} = \delta_k.$$

Therefore,

$$\begin{aligned} \|Z^\top W^{(t)} - I\| &= \sqrt{\sum_{k \in [K]} \left(\delta_k^2 + \sum_{k' \in [K] \setminus k} (Z^\top W^{(t)})_{k'k}^2 \right)} \\ &\leq \sqrt{\sum_{k \in [K]} \left(\delta_k^2 + \left(\sum_{k' \in [K] \setminus k} (Z^\top W^{(t)})_{k'k} \right)^2 \right)} \\ &\leq \sqrt{2 \sum_{k \in [K]} \delta_k^2} \leq \sqrt{2} \sum_{k \in [K]} \delta_k \\ &= \sqrt{2} \sum_{k \in [K]} \frac{\sum_{i \in \mathcal{C}_k^{(t)}} \mathbf{1}_{z_i \neq k}}{n_k^{(t)}} \\ &\leq \sqrt{2} \max_k (n_k^{(t)})^{-1} \sum_{i \in [n]} \mathbf{1}_{z_i \neq z_i^{(t)}} \\ &\stackrel{\text{Lemma 13}}{\lesssim} \frac{K}{n} h(z, z^{(t)}) \stackrel{\text{Lemma 12}}{\lesssim} K \frac{l(z, z^{(t)})}{n \Delta_{min}^2}. \end{aligned} \tag{E.1}$$

Proof of 2. Observe that with probability at least $1 - n^{-\Omega(1)}$ we have

$$\begin{aligned} \max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})^\top A W\| &\leq \max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})^\top P W\| + \max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})^\top E W\| \\ &\leq \max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})^\top Z \Pi\| + \|E W\| \max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})\| \\ &\leq \|\Pi_b\| - \sum_{j \in \mathcal{C}_b^{(t)}} \frac{\Pi_{z_j}}{n_b^{(t)}} + C \sqrt{K p_{max}} \max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})\| \\ &\lesssim \|\Pi_b\| - \sum_{j \in \mathcal{C}_b^{(t)}} \frac{\Pi_{z_j}}{n_b^{(t)}} + \frac{K^2 \sqrt{p_{max}}}{n^{1.5} \Delta_{min}^2} l(z^{(t)}, z). \end{aligned}$$

Recall that $\Delta_2^2(a, b) := \|\Pi_a - \Pi_b\|^2$. Then we have

$$\begin{aligned}
\left\| \Pi_b - \sum_{j \in \mathcal{C}_b^{(t)}} \frac{\Pi_{z_j}}{n_b^{(t)}} \right\| &= \left\| \sum_{\substack{j \in \mathcal{C}_b^{(t)} \\ b' \in [K] \setminus b}} \frac{\mathbf{1}_{\{z_j=b'\}}}{n_b^{(t)}} (\Pi_b - \Pi_{b'}) \right\| \\
&\leq C \frac{K}{n} \sum_{\substack{j \in \mathcal{C}_b^{(t)} \\ b' \in [K] \setminus b}} \max_{b, b'} \Delta_2(b, b') \mathbf{1}_{\{z_j=b'\}} \\
&\leq C \frac{K}{n} \max_{b, b'} \Delta_2(b, b') h(t, t^{(t)}) \\
&\leq C \frac{K \Delta_{min}}{\sqrt{\lambda n \Delta_{min}^2}} l(z, z^{(t)}) \quad (\text{since } \max_{b, b'} \Delta_2(b, b') \lesssim \frac{\Delta_{min}}{\sqrt{\lambda}} \text{ for SBM}) \\
&\leq C \frac{K^{1.5} \sqrt{p_{max}}}{n^{1.5} \Delta_{min}} l(z, z^{(t)}).
\end{aligned}$$

Consequently, by summing the previous bounds and using the first inequality of the Lemma we get

$$\max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})^\top A W\| \lesssim \frac{K^{1.5} \sqrt{p_{max}}}{n^{1.5} \Delta_{min}} l(z, z^{(t)}) + \frac{K^2 \sqrt{p_{max}}}{n^{1.5} \Delta_{min}^2} l(z^{(t)}, z).$$

In our setting $\Delta_{min}^2 \asymp \log n$ so the first term is dominant.

Proof of 3. First let's bound $\max_{k \in [K]} \|W_{:k}^{(t)\top} P(W - W^{(t)})\|$. By Lemma 13 we have $\|W_k^{(t)}\| \lesssim \sqrt{K/n}$, so

$$\begin{aligned}
\max_{k \in [K]} \|W_{:k}^{(t)\top} P(W - W^{(t)})\| &\leq \max_{k \in [K]} \|W_{:k}^{(t)\top} Z\| \|\Pi Z^\top (W - W^{(t)})\| \\
&\lesssim \|\Pi Z^\top (W - W^{(t)})\|_F \\
&\lesssim \sqrt{K} \max_{k \in [K]} \|(W_{:k}^{(t)} - W_{:k})^\top Z \Pi\| \\
&\lesssim \frac{K^2 \sqrt{p_{max}}}{n^{1.5} \Delta_{min}} l(z, z^{(t)}). \quad (\text{by the proof of part 2})
\end{aligned}$$

We now give an upper bound for $\max_{k \in [K]} \|W_{:k}^{(t)\top} E(W - W^{(t)})\|$. By triangle inequality,

$$\|W_{:k}^{(t)\top} E(W - W^{(t)})\| \leq \|W_{:k}^\top E(W - W^{(t)})\| + \|(W_{:k}^{(t)} - W_{:k})^\top E(W - W^{(t)})\|.$$

First we have

$$\begin{aligned}
\|W_{:k}^\top E(W - W^{(t)})\| &\leq \|W_{:k}\| \|E\| \|W - W^{(t)}\| \\
&\lesssim \frac{K^2 \sqrt{p_{max}}}{n^{1.5} \Delta_{min}^2} l(z^{(t)}, z).
\end{aligned}$$

On the other hand, we also have

$$\begin{aligned}
\|(W_{:k}^{(t)} - W_{:k})^\top E(W - W^{(t)})\| &\leq \|W_{:k} - W_{:k}^{(t)}\| \|E(W - W^{(t)})\| \\
&\leq \|E\| \sqrt{K} \max_k \|W_{:k} - W_{:k}^{(t)}\|^2 \\
&\lesssim \frac{K^{3.5} \sqrt{np_{max}} l(z^{(t)}, z)}{n^2 \Delta_{min}^2} \frac{l(z^{(t)}, z)}{n \Delta_{min}^2} \\
&\lesssim \frac{K^{3.5} \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}^2}
\end{aligned}$$

where the last inequality comes from the fact that by assumption $l(z, z^{(t)}) \leq \tau \leq \epsilon \frac{n\Delta_{min}^2}{K}$.

Thus it follows that

$$\max_{k \in [K]} \|W_{:k}^{(t)\top} P(W - W^{(t)})\| \lesssim \frac{K^2 \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}}.$$

Proof of 4. First note that

$$\begin{aligned} \|(W_{:k}^{(t)} - W_{:k})^\top P W^{(t)}\| &\leq \|(W_{:k}^{(t)} - W_{:k})^\top Z \Pi\| \|Z^\top W^{(t)}\| \\ &\lesssim \frac{K^{1.5} \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}}. \end{aligned}$$

Furthermore, by the same argument as before,

$$\begin{aligned} \|(W_{:k}^{(t)} - W_{:k})^\top E W^{(t)}\| &\leq \|(W_{:k}^{(t)} - W_{:k})^\top E (W^{(t)} - W)\| + \|(W_{:k}^{(t)} - W_{:k})^\top E W\| \\ &\lesssim K \|E\| \max_k \|W_{:k} - W_{:k}^{(t)}\|^2 + \frac{K^2 \sqrt{p_{max}}}{n^{1.5} \Delta_{min}^2} l(z^{(t)}, z) \\ &\lesssim \frac{K^2 \sqrt{p_{max}}}{n^{1.5} \Delta_{min}^2} l(z^{(t)}, z). \end{aligned}$$

We obtain the result by triangle inequality.

Proof of 5. Since $Z^\top W = I_K$ we have

$$\begin{aligned} \|Z^\top W^{(t)}\| &\leq 1 + \|Z^\top (W^{(t)} - W)\| \\ &\lesssim 1 + \|I - Z^\top W^{(t)}\| \\ &\lesssim 1 + K \frac{l(z^{(t)}, z)}{n \Delta_{min}^2} && \text{(by Equation (E.1))} \\ &\lesssim 1. && \text{(by assumption on } \tau^{(0)}) \end{aligned}$$

□

Lemma 15. For *sIR-LS* we have with probability at least $1 - n^{-\Omega(1)}$ that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(0)}$

$$\max_{k \in [K]} |n_k^{(t)} - n_k| \lesssim \frac{K\sqrt{K}}{n\Delta_{min}^2} l(z^{(t)}, z), \quad |\lambda^{(t)} - \lambda| \lesssim \lambda \frac{Kl(z^{(t)}, z)}{n\Delta_{min}^2}.$$

Proof. First observe that

$$\max_{k \in [K]} |n_k^{(t)} - n_k| = \max_{k \in [K]} \|\mathbf{1}_n^\top (W_{:k}^{(t)} - W_{:k})\| \leq \sqrt{n} \max_{k \in [K]} \|W_{:k}^{(t)} - W_{:k}\| \leq \frac{K\sqrt{K}}{n\Delta_{min}^2} l(z^{(t)}, z)$$

by Lemma 14.

Then note that we have

$$\begin{aligned}
|p_{max}^{(t)} - p_{max}| &\leq \max_{k,k'} \|(W_{:k}^{(t)})^\top A W_{:k'}^{(t)} - W_{:k}^\top P W_{:k'}\| && \text{(the max is 1-Lipschitz)} \\
&\leq \max_{k,k'} (\|(W_{:k}^{(t)})^\top E W_{:k'}^{(t)}\| + \|(W_{:k}^{(t)} - W_{:k})^\top P W_{:k'}^{(t)}\| + \|W_{:k}^\top P (W_{:k'}^{(t)} - W_{:k'})\|) \\
&\lesssim \max_k \|W_{:k}^{(t)}\|^2 \|E\| + \frac{K^{1.5} \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}} && \text{(by the proof of Lemma 14)} \\
&\lesssim \frac{K \sqrt{p_{max}}}{\sqrt{n}} + \frac{K^{1.5} \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}} \\
&\lesssim \frac{K^{1.5} \sqrt{p_{max}} l(z^{(t)}, z)}{n^{1.5} \Delta_{min}} \\
&\lesssim \sqrt{\frac{K}{n p_{max}} \frac{Kl(z^{(t)}, z)}{n \Delta_{min}}} p_{max} \\
&\lesssim \frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2} p_{max}
\end{aligned}$$

since $\Delta_{min} \asymp \sqrt{\log n / K}$. Consequently,

$$\begin{aligned}
\left| \frac{\lambda^{(t)}}{\lambda} - 1 \right| &\leq \left| \frac{n_{min}^{(t)} p_{max} - 1}{n_{min} p_{max}} \right| \\
&\leq \left| \frac{n_{min}^{(t)} - n_{min}}{n_{min}} \frac{p_{max}}{p_{max}} \right| + \left| \frac{p_{max} - p_{max}^{(t)}}{p_{max}^{(t)}} \right| \\
&\lesssim \frac{\sqrt{K}}{n^2 \Delta_{min}^2} l(z^{(t)}, z) + \frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2} \\
&\lesssim \frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2}.
\end{aligned}$$

□

Lemma 16. For IR-LSS, we have with probability at least $1 - n^{-\Omega(1)}$ that for all $z^{(t)}$ such that $l(z^{(t)}, z) \leq \tau^{(0)}$

$$|\lambda^{(t)} - \lambda| \lesssim \lambda \frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2}$$

Proof. By a similar argument as the one used in Lemma 15 we have with probability at least $1 - n^{-\Omega(1)}$ that

$$|p^{(t)} - p| \lesssim \frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2} p, \quad |q^{(t)} - q| \lesssim \frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2} q.$$

This implies

$$\frac{p^{(t)} - q^{(t)}}{p - q} = 1 + O\left(\frac{(p+q)Kl(z^{(t)}, z)}{(p-q)n \Delta_{min}^2}\right) = 1 + O\left(\frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2}\right)$$

because $p - q \gtrsim p$. Thus,

$$\left| \log\left(\frac{p^{(t)}}{q^{(t)}}\right) - \log\left(\frac{p}{q}\right) \right| = \left| \log\left(\frac{p^{(t)}}{p} \frac{q}{q^{(t)}}\right) \right| = 2 \log\left(1 + O\left(\frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2}\right)\right) = O\left(\frac{Kl(z^{(t)}, z)}{n \Delta_{min}^2}\right).$$

Hence

$$\left| \frac{\log\left(\frac{p^{(t)}}{q^{(t)}}\right)}{\log\left(\frac{p}{q}\right)} - 1 \right| = O\left(\frac{K^{1.5} l(z^{(t)}, z)}{n \Delta_{min}^2}\right)$$

since $\log(p/q)$ is bounded above by assumption. Consequently,

$$\frac{\lambda^{(t)}}{\lambda} - 1 = O\left(\frac{Kl(z^{(t)}, z)}{n\Delta_{min}^2}\right).$$

□

F Additional experiments

F.1 Heterophilic SBM

If we disregard the covariates, our algorithm can be used for inference under a general SBM, in contrast to the method proposed by Lu and Zhou (2016) which was restricted to the assortative setting. In particular, our algorithm also works for networks with heterophilic communities. The following experiment illustrates the gain in term of accuracy for IR-LS initialized with A-SC (spectral clustering on the adjacency matrix). It also shows the interest of using more than one iteration in the refinement step with the MAP (this corresponds to IR-MAP(1)).

We consider $n = 1000$, $K = 3$, $Z_i \stackrel{i.i.d}{\sim} \text{Multinomial}(1; 1/3, 1/3, 1/3)$ and

$$\Pi = \begin{pmatrix} 0.2 & 0.05 & 0.1 \\ 0.05 & 0.15 & 0.05 \\ 0.1 & 0.05 & 0.03 \end{pmatrix}.$$

The NMI is averaged over 40 repetitions; the results are shown in Figure 4. We also considered the VEM algorithm implemented in the R package `blockmodels` (Léger, 2016), but the running time was prohibitive (approximately one hour for a single Monte Carlo run, whereas our algorithm take a few seconds). It nevertheless returned the exact partition as IR-LS.

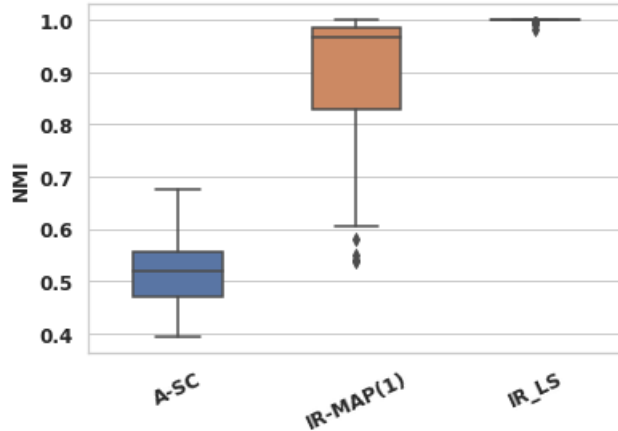


Figure 4: Average performance of different algorithms on a heterophilic SBM, over 40 Monte Carlo runs.

F.2 Australian Rainfall

We reproduced the experiment presented in Section 5 but with $K \in \{3, 7, 10\}$ (see Figures 5, 6 and 7). We can observe that sIR-LS provides a visibly better clustering than that by IR-LS. This can possibly be attributed to the fact that IR-LS requires estimating more parameters than sIR-LS, however this dataset is quite small in size. Furthermore, the partition provided by K-means is visibly different than that generated by sIR-LS, `Sponge-sym` and `Iter-SBM` (although there is still some overlap) since K-means uses only covariate information.

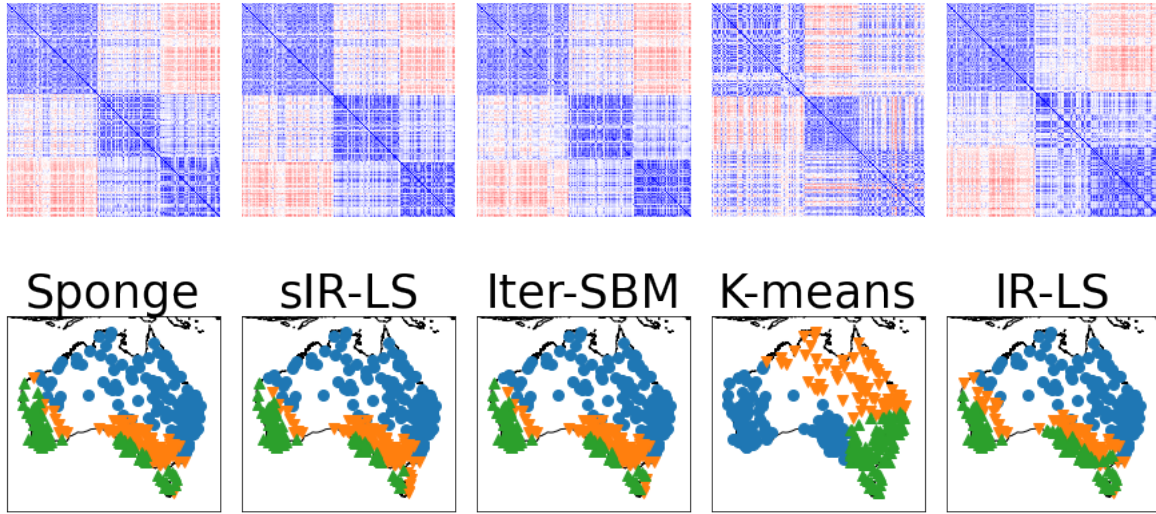


Figure 5: Sorted adjacency matrices of the Australian rainfall data set and corresponding maps for $K = 3$.

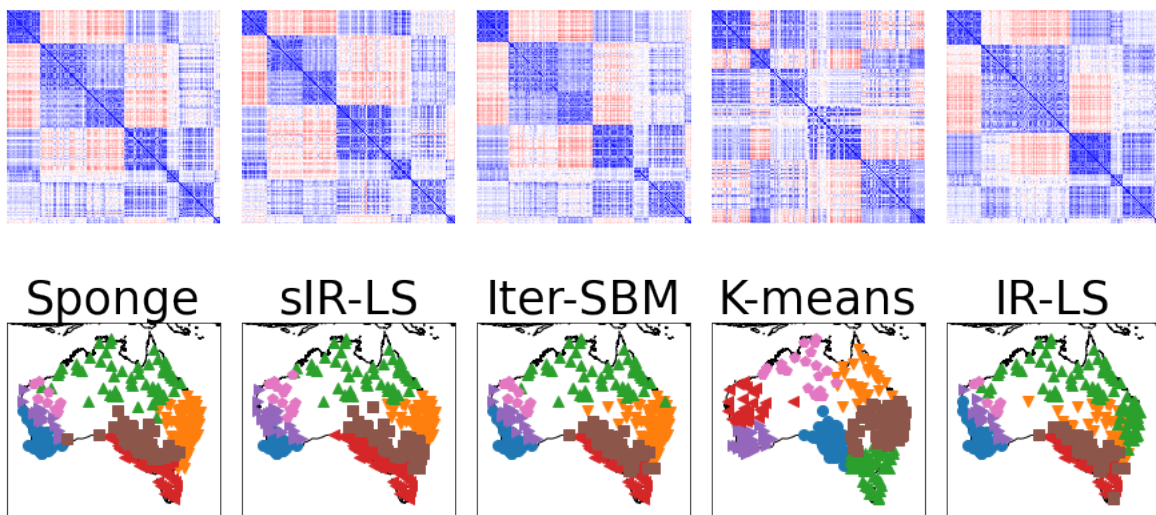


Figure 6: Sorted adjacency matrices of the Australian rainfall data set and corresponding maps for $K = 7$.

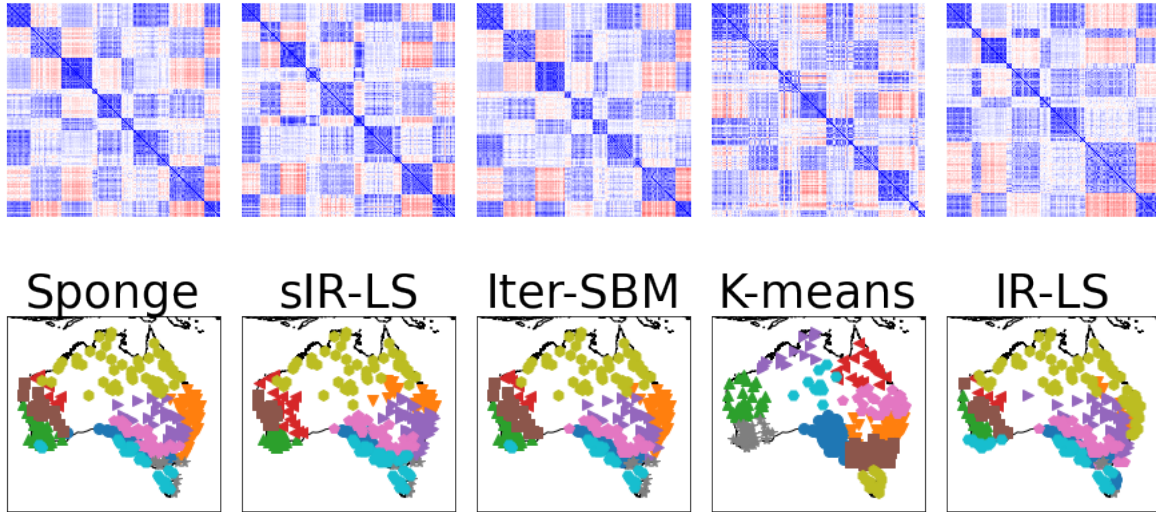


Figure 7: Sorted adjacency matrices of the Australian rainfall data set and corresponding maps for $K = 10$.

F.3 Signed SBM

We reproduced the experiment presented in Section 5.2 at a different sparsity level $p = 0.03$. The relative performance of the methods (shown in Figure 8) are similar to that in Figure 2. Algorithm 3 outlines our iterative refinement method (namely IR-SSBM) for clustering signed graphs, under the Signed SBM. It seems that there is a threshold for the noise level η above which no algorithm can succeed. We conjecture that IR-SSBM is optimal and attains this threshold.

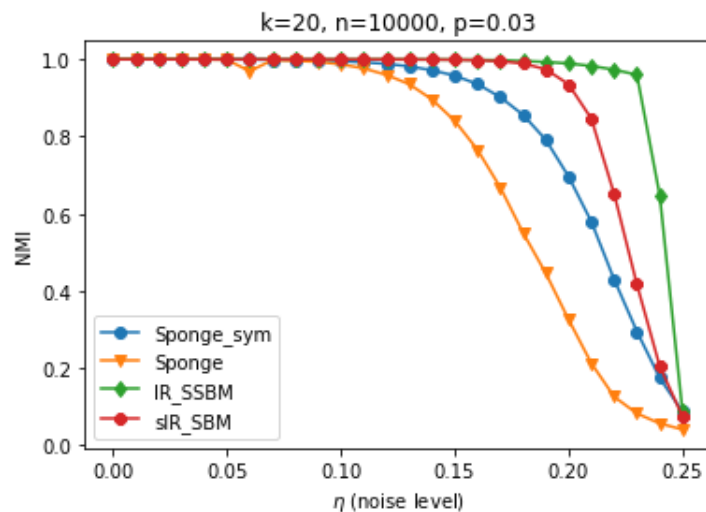


Figure 8: NMI for varying noise η , and with $p = 0.03$, $K = 20$, $n = 10000$.

Algorithm 3 IR-SBM

Input: The number of communities K , initial partition $z^{(0)}$, $T \geq 1$.

- 1: **for** $0 \leq t \leq T - 1$ **do**
- 2: Compute $W^{(t)} = Z^{(t)}(D^{(t)})^{-1}$ where $D^{(t)} = \text{diag}(n_k^{(t)})_{k \in [K]}$, and $C^{(t)} = AW^{(t)}$.
- 3: Update the partition for each $i \leq n$

$$z_i^{(t+1)} = \arg \max_k C_{ik}^{(t)}$$

- 4: **end for**

Output: A partition of the nodes $z^{(T)}$.

F.4 Not distinguishable community

We repeated the experiment of Section 5.1 with the rank deficient connectivity matrix

$$\Pi = 0.02 * \begin{pmatrix} 1.5 & 1.5 & 0.5 \\ 1.5 & 1.5 & 0.5 \\ 0.05 & 0.05 & 1.5 \end{pmatrix}$$

but with the same covariate parameters as in Section 5.1. Not surprisingly, we obtained similar results (see Figure 9) as in Figure 1. The main difference is that the performance of ORL-SC worsened.

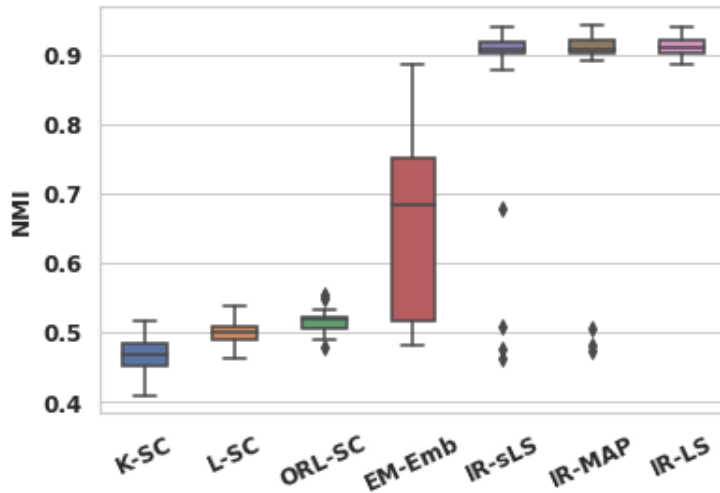


Figure 9: Performance of different algorithms on CSBM. Results are sorted by mean NMI and obtained over 40 runs.