

APPENDIX A
PROOFS

A. Proof of Lemma 1

Before we prove Lemma 1, we introduce two useful lemmas firstly.

Lemma 2.

$$\mathbf{Q}^T \mathbf{D}^{-1} \mathbf{Q} = \mathbf{D}_s^{-1}, \quad (19)$$

where \mathbf{Q} is the reconstruction matrix in the configuration-based reconstruction scheme (see Equation (7)), \mathbf{D} and \mathbf{D}_s are degree matrix of the original graph and the summary graph.

Proof: The (p, q) -th entry in $\mathbf{Q}^T \mathbf{D}^{-1} \mathbf{Q}$ is:

$$\mathbf{Q}^T \mathbf{D}^{-1} \mathbf{Q}(p, q) = \sum_i \mathbf{Q}(i, p) \frac{1}{d_i} \mathbf{Q}(i, q) \quad (20)$$

It is easy to see that the result is not zero only when $p = q$ (since a node i cannot belongs to two supernodes \mathcal{S}_p and \mathcal{S}_q simultaneously). And diagonal items are (note that $d_p^{(s)} = \sum_{v_i \in \mathcal{S}_p} d_i$):

$$\begin{aligned} \mathbf{Q}^T \mathbf{D}^{-1} \mathbf{Q}(p, p) &= \sum_{v_i \in \mathcal{S}_p} \mathbf{Q}(i, p) \frac{1}{d_i} \mathbf{Q}(i, p) \\ &= \sum_{v_i \in \mathcal{S}_p} \frac{d_i}{d_p^{(s)}} \frac{1}{d_i} \frac{d_i}{d_p^{(s)}} \\ &= \sum_{v_i \in \mathcal{S}_p} \frac{d_i}{d_p^{(s)}} \frac{1}{d_p^{(s)}} \\ &= \frac{1}{d_p^{(s)}} = \mathbf{D}_s^{-1}(p, p) \end{aligned} \quad (21)$$

Lemma 3.

$$\mathbf{R} \mathbf{D}_s^{-c} = \mathbf{D}^{-c} \mathbf{Q} \quad (22)$$

Proof: Suppose $v_i \in \mathcal{S}_p$, then the (i, p) -th entry of $\mathbf{R} \mathbf{D}_s^{-c}$ is:

$$\mathbf{R} \mathbf{D}_s^{-c}(i, p) = \left(\frac{d_i}{d_p^{(s)}} \right)^{1-c} \left(d_p^{(s)} \right)^{-c} = \frac{d_i^{1-c}}{d_p^{(s)}}$$

And the (i, p) -th entry of $\mathbf{D}^{-c} \mathbf{Q}$ is:

$$\mathbf{D}^{-c} \mathbf{Q}(i, p) = (d_i)^{-c} \frac{d_i}{d_p^{(s)}} = \frac{d_i^{1-c}}{d_p^{(s)}}$$

Thus $\mathbf{R} \mathbf{D}_s^{-c} = \mathbf{D}^{-c} \mathbf{Q}$. ■

Proof of Lemma 1:

Proof: Denote $\mathcal{K}_\tau(\mathcal{G}) = (\mathbf{D}^{-c} \mathbf{A}_r \mathbf{D}^{-1+c})^\tau \mathbf{D}^{1-2c}$ for convenience. Prove by induction. When $\tau = 1$,

$$\begin{aligned} \mathcal{K}_1(\mathcal{G}_r) &= \mathbf{D}^{-c} \mathbf{A}_r \mathbf{D}^{-1+c} \mathbf{D}^{1-2c} \\ &= \mathbf{D}^{-c} \mathbf{Q} \mathbf{A}_s \mathbf{Q}^T \mathbf{D}^{-c} \quad (\text{Lemma 3}) \\ &= \mathbf{R} \mathbf{D}_s^{-c} \mathbf{A}_s \mathbf{D}_s^{-c} \mathbf{R}^T \\ &= \mathbf{R} \mathcal{K}_1(\mathcal{G}_s) \mathbf{R}^T \end{aligned}$$

Suppose the lemma holds for $\tau = i$, i.e., $\mathcal{K}_i(\mathcal{G}_r) = \mathbf{R} \mathcal{K}_i(\mathcal{G}_s) \mathbf{R}^T$. For the case $\tau = i + 1$,

$$\begin{aligned} \mathcal{K}_{i+1}(\mathcal{G}_r) &= \mathbf{D}^{-c} \mathbf{A}_r \mathbf{D}^{-1+c} \mathcal{K}_i(\mathcal{G}_r) \quad (\text{By induction hypothesis}) \\ &= \mathbf{D}^{-c} \mathbf{A}_r \mathbf{D}^{-1+c} \mathbf{R} \mathcal{K}_i(\mathcal{G}_s) \mathbf{R}^T \\ &= \mathbf{D}^{-c} \mathbf{Q} \mathbf{A}_s \mathbf{Q}^T \mathbf{D}^{-1+c} \mathbf{R} \mathcal{K}_i(\mathcal{G}_s) \mathbf{R}^T \\ &= \mathbf{D}^{-c} \mathbf{Q} \mathbf{A}_s \mathbf{Q}^T \mathbf{D}^{-1} (\mathbf{D}^c \mathbf{R}) \mathcal{K}_i(\mathcal{G}_s) \mathbf{R}^T \\ &= \mathbf{D}^{-c} \mathbf{Q} \mathbf{A}_s \mathbf{Q}^T \mathbf{D}^{-1} (\mathbf{Q} \mathbf{D}_s^c) \mathcal{K}_i(\mathcal{G}_s) \mathbf{R}^T \end{aligned}$$

(Lemma 2 and 3.)

$$\begin{aligned} &= \mathbf{R} \mathbf{D}_s^{-c} \mathbf{A}_s \mathbf{D}_s^{-1+c} \mathcal{K}_i(\mathcal{G}_s) \mathbf{R}^T \\ &= \mathbf{R} \mathcal{K}_{i+1}(\mathcal{G}_s) \mathbf{R}^T \end{aligned}$$

Applying principal of induction finishes the proof. ■

B. Further details in proof of Thm. 1 and 2

Proposition 1. $\log(\mathbf{R} \mathbf{M} \mathbf{R}^T) = \mathbf{R} \log(\mathbf{M}) \mathbf{R}^T$, where \mathbf{R} is defined in Eq. (12), and \mathbf{M} is a $n_s \times n_s$ matrix.

Proof: Suppose $v_i \in \mathcal{S}_p, v_j \in \mathcal{S}_q$, the (i, j) -th entry of $\log(\mathbf{R} \mathbf{M} \mathbf{R}^T)$ is:

$$\begin{aligned} \log(\mathbf{R} \mathbf{M} \mathbf{R}^T)(i, j) &= \log(\mathbf{R}(i, p) \cdot \mathbf{M}(p, q) \cdot \mathbf{R}(j, q)) \\ &= \log(1 \cdot \mathbf{M}(p, q) \cdot 1) \\ &= \log(\mathbf{M}(p, q)) \end{aligned}$$

$$\begin{aligned} \mathbf{R} \log(\mathbf{M}) \mathbf{R}^T(i, j) &= \mathbf{R}(i, p) \log \mathbf{M}(p, q) \mathbf{R}(j, q) \\ &= \log(\mathbf{M}(p, q)) \\ &= \log(\mathbf{R} \mathbf{M} \mathbf{R}^T)(i, j) \end{aligned}$$

Proposition 2. $\sigma(\mathbf{R} \mathbf{M}) = \mathbf{R} \cdot \sigma(\mathbf{M})$, where \mathbf{R} is defined in Eq. (14), and \mathbf{M} is a $n_s \times d$ matrix. $\sigma(\cdot)$ is ReLU function. ■

Proof: Suppose $v_i \in \mathcal{S}_p$, the i -th row of $\sigma(\mathbf{R} \mathbf{M})$ is:

$$\begin{aligned} \sigma(\mathbf{R} \mathbf{M})(i, :) &= \sigma\left(\frac{d_i}{d_p^{(s)}} \mathbf{M}(p, :)\right) \\ &= \frac{d_i}{d_p^{(s)}} \sigma(\mathbf{M}(p, :)) \\ &= \mathbf{R} \sigma(\mathbf{M})(i, :) \end{aligned}$$

APPENDIX B
DETAILS OF DPGS ALGORITHM

In GELSUMM, we use a graph summarization method DPGS, which minimizes the total description length of both the model cost and configuration-based reconstruction error.

$$L(M, D) = L(M) + L(D | M) \quad (23)$$

Here $L(M, D)$ is the total description length which consists of two parts, model part $L(M)$ and error part $L(D | M)$.

$${}^6 \mathbf{D}^{-c} \mathbf{Q} = \mathbf{R} \mathbf{D}_s^{-c} \Rightarrow \mathbf{Q} = \mathbf{D}^c \mathbf{R} \mathbf{D}_s^{-c} \Rightarrow \mathbf{Q} \mathbf{D}_s^c = \mathbf{D}^c \mathbf{R}.$$

The error part is measured by KL divergence:

$$\begin{aligned}
L(D \mid M) &= \text{KL}(A \parallel A_r) \\
&= \sum_{i,j} A(i,j) \ln \frac{A(i,j)}{A_r(i,j)} - A(i,j) + A_r(i,j) \\
&= \sum_{i,j} A(i,j) \ln \frac{A(i,j)}{A_r(i,j)},
\end{aligned} \tag{24}$$

where A_r is the reconstructed adjacency matrix under configuration-based reconstruction scheme (see Eq. (8)).

For model part, we encode the number of

$$L(M) = L_{\mathbb{N}}(n_s) + n L_{\mathbb{N}}(n_s) + \sum_{i=1}^n L_{\mathbb{N}}(d_i) + L(A_S), \tag{25}$$

where $L_{\mathbb{N}}(n)$ is the encoding length for an integer n .

In each iteration of the algorithm, nodes pair are sampled and merged. The complete process is described in Algorithm 4.

Algorithm 4 MergeGroup

Input: $g \subset V_S$

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1:  $times \leftarrow \log_2 |g|$ 
2:  $nskip \leftarrow 0$ 
3: while  $nskip < times$  and  $|g| \geq 1$  do
4:    $pairs \leftarrow \text{Sample } \log_2 |g| \text{ node pairs from } g$ 
5:    $u, v \leftarrow \arg \max_{(i,j) \in pairs} gain(i, j)$ 
6:   if  $gain(u, v) > 0$  then
7:     Merge  $u$  and  $v$ 
8:      $nskip \leftarrow 0$ 
9:   else
10:     $nskip \leftarrow nskip + 1$ 
11:   end if
12: end while

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