DPGS: Degree-Preserving Graph Summarization (Appendix)

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A Analysis of $\Delta L_E(i,j)$

Assumed that the input graphs are simple and undirected, the error description length $L(D \mid M)$ is:

(A.1)
$$L(D \mid M) = \sum_{(i,j)\in E} \ln \frac{1}{\frac{d_i}{D_k} A_S(k,l) \frac{d_j}{D_l}} \\ = \sum_{(i,j)\in E} \ln \frac{D_k D_l}{A_S(k,l)} - \sum_{(i,j)\in E} \ln(d_i d_j).$$

Since the second term only depends on the input graph, we only consider the first term in the following.

(A.2)
$$L(D \mid M) = \sum_{(i,j) \in E} \ln \frac{D_k D_l}{A_S(k,l)}$$

$$= 2 \sum_{k=1}^{n_s} D_k \ln D_k - \sum_{k=1}^{n_s} \sum_{l=1}^{n_s} A_S(k,l) \ln A_S(k,l).$$

Suppose the current supernode set is S. After merging supernodes S_i and S_j into a new supernode S_k , we get a new supernode set $S' = S \setminus \{S_i, S_j\} \cup \{S_k\}$. The connectivity of S_k is the aggregation of S_i and S_j , that is,

(A.3)
$$A_S(k,l) = \begin{cases} A_S(i,l) + A_S(j,l) & l \neq k \\ A_S(i,i) + A_S(j,j) + 2A_S(i,j) & l = k \end{cases}.$$

Now we expand the $\Delta L_E(i,j)$ as follow (we define $f(x) = x \ln x (x > 0)$ and f(0) = 0 for simplicity):

$$\Delta L_{E}(i,j) = L(D \mid M') - L(D \mid M)$$

$$= 2(f(D_{i} + D_{j}) - f(D_{i}) - f(D_{j}))$$

$$+ 2 \sum_{l \in \mathcal{S}, l \neq i, j} [f(A_{S}(i,l)) + f(A_{S}(j,l))]$$

$$- 2 \sum_{l \in \mathcal{S}', l \neq k} f(A_{S}(k,l))$$

$$+ f(A_{S}(i,i)) + f(A_{S}(i,j)) + 2f(A_{S}(i,j))$$

$$- f(A_{S}(k,k)).$$

Note that if S_l is not the common neighbor of supernode S_i and S_j , it makes no contribution to $\Delta L_E(i,j)$. Each common neighbors makes positive contribution to $\Delta L_E(i,j)$ (since f(x+y) > f(x) + f(y) for $x,y \ge 1$). Thus, the more common neighbors supernodes S_i and S_j have, the more likely the merging cost $\Delta L_E(i,j)$ is small.

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B PROOFS

B.1 Proof of Theorem 3.1

Proof. Denote the normalized Laplacian matrix of the original graph and the reconstructed graph as \mathcal{L} and \mathcal{L}' . By [?], the squared error between eigenvalues of \mathcal{L} and \mathcal{L}' are bounded by:

(B.5)
$$\sum_{i=1}^{n} (\lambda(i) - \lambda'(i))^{2} \le \|\mathcal{L} - \mathcal{L}'\|_{F}^{2}$$

$$\|\mathcal{L} - \mathcal{L}'\|_F^2 = \sum_{i=1}^n \sum_{j=1}^n |\mathcal{L}(i,j) - \mathcal{L}'(i,j)|^2$$

$$= \sum_{i=1}^n \sum_{j=1}^n \left(\frac{A(i,j)}{\sqrt{d_i d_j}} - \frac{A'(i,j)}{\sqrt{d_i d_j}} \right)^2$$

$$\leq \sum_{i=1}^n \sum_{j=1}^n \left(\frac{A(i,j)}{\sqrt{d_i}} - \frac{A'(i,j)}{\sqrt{d_i}} \right)^2$$

$$= \sum_{i=1}^n \sum_{j=1}^n d_i \left(\frac{A(i,j)}{d_i} - \frac{A'(i,j)}{d_i} \right)^2$$

Denote the normalized *i*-th row of A and A' as $\tilde{A}(i)$ and $\tilde{A}'(i)$, then $\tilde{A}(i)$ and $\tilde{A}'(i)$ can be seen as two distributions. Moreover, with the following inequality [?]:

(B.6)
$$D_{KL}(p||q) = \sum_{i} p_i \log_2 \frac{p_i}{q_i} \ge \frac{1}{2 \ln 2} ||p - q||_1^2,$$

we have¹

$$\|\mathcal{L} - \mathcal{L}'\|_F^2 = \sum_{i=1}^n d_i \cdot \|\tilde{A} - \tilde{A}'\|_1^2$$

$$\leq 2 \ln 2 \sum_{i=1}^n d_i \cdot D_{KL}(\tilde{A} \| \tilde{A}')$$

$$= 2 \cdot \sum_{i=1}^n d_i \cdot \sum_{j=1}^n \frac{A(i,j)}{d_i} \ln \frac{A(i,j)}{A'(i,j)}$$

$$= 2 \cdot \sum_{i=1}^n \sum_{j=1}^n A(i,j) \ln \frac{A(i,j)}{A'(i,j)}$$

$$= 2 \cdot L(D | M)$$

Together, we have

(B.7)
$$\sum_{i=1}^{n} (\lambda(i) - \lambda'(i))^2 \le 2 \cdot L(D \mid M)$$

The base of logarithm of Inequality (??) is 2, thus the factor ln 2 vanished since we change the base from 2 to e.

B.2 Proof of Theorem 3.2

Proof. The key tool is Jensen's inequality. Suppose f(x) is a convex function, then

(B.8)
$$f(\frac{\sum_{i} \lambda_{i} x_{i}}{\sum_{i} \lambda_{i}}) \leq \frac{\sum_{i} \lambda_{i} f(x_{i})}{\sum_{i} \lambda_{i}},$$

where λ_i is positive weights.

In the following proof, the inequality is applied on $f(x) = -\ln x$.

$$\Delta L_{E}(i,j) = 2 \left(D_{i} \ln \frac{D_{i} + D_{j}}{D_{i}} + D_{j} \ln \frac{D_{i} + D_{j}}{D_{j}} \right)$$

$$+ 2 \sum_{l \neq i,j} \left(A_{S}(i,l) \ln \frac{A_{S}(i,l)}{A_{S}(i,l) + A_{S}(j,l)} + A_{S}(j,l) \ln \frac{A_{S}(j,l)}{A_{S}(i,l) + A_{S}(j,l)} \right)$$

$$+ A_{S}(i,i) \ln \frac{A_{S}(i,i)}{A_{S}(i,i) + A_{S}(j,j) + 2A_{S}(i,j)} + A_{S}(j,j) \ln \frac{A_{S}(j,j)}{A_{S}(i,i) + A_{S}(j,j) + 2A_{S}(i,j)}$$

$$+ 2A_{S}(i,j) \ln \frac{A_{S}(i,j)}{A_{S}(i,i) + A_{S}(j,j) + 2A_{S}(i,j)}$$

Let's focused on the part related to i in Equation (??), since i and j are symmetric.

$$\Delta L_{E}(i,j)_{i} = 2D_{i} \ln \frac{D_{i} + D_{j}}{D_{i}}$$

$$+ 2 \sum_{l \neq i,j} \left(A_{S}(i,l) \ln \frac{A_{S}(i,l)}{A_{S}(i,l) + A_{S}(j,l)} \right)$$

$$+ A_{S}(i,i) \ln \frac{A_{S}(i,i)}{A_{S}(i,i) + A_{S}(j,j) + 2A_{S}(i,j)}$$

$$+ A_{S}(i,j) \ln \frac{A_{S}(i,j)}{A_{S}(i,j) + A_{S}(j,j) + 2A_{S}(i,j)}$$

Apply Jensen's inequality on the last two row

$$\begin{split} & \geq 2D_{i} \ln \frac{D_{i} + D_{j}}{D_{i}} \\ & + 2 \sum_{l \neq i, j} \left(A_{S}(i, l) \ln \frac{A_{S}(i, l)}{A_{S}(i, l) + A_{S}(j, l)} \right) \\ & + 2(A_{S}(i, i) + A_{S}(i, j)) \cdot \left(-\ln \frac{A_{S}(i, i) + A_{S}(j, j) + 2A_{S}(i, j)}{A_{S}(i, i) + A_{S}(i, j)} \right) \\ & = 2D_{i} \left[\sum_{l \neq i, j} \frac{A_{S}(i, l)}{D_{i}} \cdot \left(-\ln \frac{A_{S}(i, l) + A_{S}(j, l)}{A_{S}(i, l)} \frac{D_{i}}{D_{i} + D_{j}} \right) \right. \\ & \left. + \frac{A_{S}(i, i) + A_{S}(i, j)}{D_{i}} \cdot \left(-\ln \frac{A_{S}(i, i) + A_{S}(j, j) + 2A_{S}(i, j)}{A_{S}(i, i) + A_{S}(i, j)} \frac{D_{i}}{D_{i} + D_{j}} \right) \right] \end{split}$$

Apply Jensen's inequality again

$$\geq 2D_{i} \cdot \left(-\ln \left[\sum_{l \neq i, j} \frac{A_{S}(i, l) + A_{S}(j, l)}{D_{i} + D_{j}} + \frac{A_{S}(i, i) + A_{S}(j, j) + 2A_{S}(i, j)}{D_{i} + D_{j}}\right]\right)$$

$$= 2D_{i} \cdot (-\ln 1)$$

$$= 0$$

Similarly, $\Delta L_E(i,j)_j \geq 0$. Together, $\Delta L_E(i,j) \geq 0$.