

# Supplement for “New Insights into Laplacian Similarity Search”

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## Abstract

*This is the supplement for our main paper “New Insights into Laplacian Similarity Search” [3]. Here, we show the proofs of all the theoretical arguments in the main paper.*

**Proof of Statements in Sec. 2.1:**  $M$  is positive and symmetric, i.e.,  $\forall i, j, m_{ij} > 0$ , and  $m_{ij} = m_{ji}$ . Regardless of  $\Lambda$ ,  $m_{ii}$  is always the unique largest element in the  $i$ -th column and row of  $M$ .

*Proof.* (a) Since  $L + \alpha\Lambda$  is symmetric,  $M = (L + \alpha\Lambda)^{-1}$  is symmetric.

(b) Note that

$$\begin{aligned} M &= (L + \alpha\Lambda)^{-1} = (D + \alpha\Lambda - W)^{-1} \\ &= (I - (D + \alpha\Lambda)^{-1}W)^{-1}(D + \alpha\Lambda)^{-1} \\ &= \left( \sum_{k=0}^{\infty} [((D + \alpha\Lambda)^{-1})W]^k \right) (D + \alpha\Lambda)^{-1}, \end{aligned}$$

from which we can see that  $M$  is positive since the graph is connected.

(c) Now we show that  $m_{jj}$  is the unique largest in its column. Assume, to the contrary, there exists  $i, j, i \neq j$ , such that  $m_{jj} \leq m_{ij}$ . Denote  $k = \arg \max_{i \neq j} m_{ij}$ . Note that  $M$  is symmetric and  $M > 0$ . Let  $B = (b_{ij}) := D + \alpha\Lambda - W$ . Note that  $B$  is symmetric and strictly diagonally dominant, i.e.,  $\forall k, b_{kk} > \sum_{i \neq k} |b_{ki}|$ . By  $BM = I$ , we have  $0 = B(k, :)M(:, j) = \sum_i b_{ki}m_{ij} = b_{kk}m_{kj} + \sum_{i \neq k} b_{ki}m_{ij} \geq b_{kk}m_{kj} - (\sum_{i \neq k} |b_{ki}|)m_{kj} = (b_{kk} - \sum_{i \neq k} |b_{ki}|)m_{kj} > 0$ , which contradicts the assumption.  $\square$

## Proof of Theorem 2.1:

$$\begin{aligned} M &= C + E, \text{ where } C = \frac{1}{\alpha \sum_i \lambda_i} \mathbf{1}\mathbf{1}^\top, \text{ and } E = \\ &= \Lambda^{-\frac{1}{2}} \left( \sum_{i=2}^n \frac{1}{\gamma_i + \alpha} \mathbf{u}_i \mathbf{u}_i^\top \right) \Lambda^{-\frac{1}{2}}. \end{aligned}$$

*Proof.* By definition,

$$\begin{aligned} M &= (L + \alpha\Lambda)^{-1} \\ &= \Lambda^{-\frac{1}{2}} (\Lambda^{-\frac{1}{2}} L \Lambda^{-\frac{1}{2}} + \alpha I)^{-1} \Lambda^{-\frac{1}{2}} \\ &= \Lambda^{-\frac{1}{2}} \left( \sum_{i=1}^n (\gamma_i + \alpha) \mathbf{u}_i \mathbf{u}_i^\top \right)^{-1} \Lambda^{-\frac{1}{2}} \\ &= \Lambda^{-\frac{1}{2}} \left( \sum_{i=1}^n \frac{1}{\gamma_i + \alpha} \mathbf{u}_i \mathbf{u}_i^\top \right) \Lambda^{-\frac{1}{2}} \\ &= \frac{1}{\alpha \sum_i \lambda_i} \mathbf{1}\mathbf{1}^\top + \Lambda^{-\frac{1}{2}} \left( \sum_{i=2}^n \frac{1}{\gamma_i + \alpha} \mathbf{u}_i \mathbf{u}_i^\top \right) \Lambda^{-\frac{1}{2}}. \end{aligned}$$

$\square$

**Proof of Corollary 2.2:**  $\lim_{\alpha \rightarrow 0} E = \Lambda^{-\frac{1}{2}} \bar{L}^\dagger \Lambda^{-\frac{1}{2}}$ .

*Proof.* It follows from  $\bar{L}^\dagger = \sum_{i=2}^n \frac{1}{\gamma_i} \mathbf{u}_i \mathbf{u}_i^\top$ .  $\square$

## Proof of Statements in Sec. 2.1:

Ranking by  $(h_{ij})_{i=1, \dots, n}$  is equivalent as ranking by the  $j$ -th column of  $D^{-\frac{1}{2}} L_{sym}^\dagger D^{-\frac{1}{2}}$ .

*Proof.* Let  $e_i$  denote the  $i$ -th unit vector in  $\mathbb{R}^n$ . The hitting time that a random walk from vertex  $i$  to hit vertex  $j$  can be computed by [1]:

$$\begin{aligned} H_{ij} &= d(\mathcal{V}) \left\langle \frac{1}{\sqrt{d_j}} e_j, L_{sym}^\dagger \left( \frac{1}{\sqrt{d_j}} e_j - \frac{1}{\sqrt{d_i}} e_i \right) \right\rangle \\ &= d(\mathcal{V}) \left( \frac{1}{d_j} e_j^\top L_{sym}^\dagger e_j - \frac{1}{\sqrt{d_i} \sqrt{d_j}} e_i^\top L_{sym}^\dagger e_j \right). \end{aligned}$$

Thus given  $j$ , ranking by  $(h_{ij})_{i=1, \dots, n}$  is determined by  $-\frac{1}{\sqrt{d_i} \sqrt{d_j}} e_i^\top L_{sym}^\dagger e_j$ . Denote by  $B = (b_{ij}) := D^{-\frac{1}{2}} L_{sym}^\dagger D^{-\frac{1}{2}}$ . Then  $b_{ij} = \frac{1}{\sqrt{d_i} \sqrt{d_j}} e_i^\top L_{sym}^\dagger e_j$ . This shows that ranking by  $(h_{ij})_{i=1, \dots, n}$  in ascending order is the same as ranking by  $(b_{ij})_{i=1, \dots, n}$  in descending order. Note that a smaller  $h_{ij}$  means vertices  $i$  and  $j$  are closer on the graph.  $\square$



## References

- [1] U. von Luxburg, A. Radl, and M. Hein. Hitting and commute times in large random neighborhood graphs. *Journal of Machine Learning Research*, 15:1751–1798, 2014. [1](#)
- [2] X.-M. Wu, Z. Li, and S.-F. Chang. Analyzing the harmonic structure in graph-based learning. In *NIPS*, 2013. [2](#)
- [3] X.-M. Wu, Z. Li, and S.-F. Chang. New insights into laplacian similarity search. In *CVPR*, 2015. [1](#)