Appendix of "Clustering Ensemble via Structured Hypergraph Learning"

Peng Zhou^{a,b}, Xia Wang^a, Liang Du^c, Xuejun Li^a

^aSchool of Computer Science and Technology, Anhui University, Hefei 230601, China. ^bThe State Key Laboratory of Computer Science, Institute of Software, Chinese Academy of Sciences, Beijing 100190, China ^cSchool of Computer and Information Technology, Shanxi University, Taiyuan 030006, China

Proof of Theorem 1

Theorem 1. Given any hypergraph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}, \mathbf{W}\}$ with *n* nodes, if the rank of its Laplacian matrix **L**, which is defined as $\mathbf{L} = \mathbf{I} - \mathbf{D}_v^{-\frac{1}{2}} \mathbf{Y} \mathbf{W} \mathbf{D}_e^{-1} \mathbf{Y}^T \mathbf{D}_v^{-\frac{1}{2}}$, is n - c, then \mathcal{G} contains exact *c* connective components.

⁵ *Proof.* Before proving this Theorem, we provide the following lemma:

Lemma 1. Given any connective hypergraph $\mathcal{G} = {\mathcal{V}, \mathcal{E}, \mathbf{W}}$ with *n* nodes (i.e., \mathcal{G} only contains one connective component), the rank of its Laplacian matrix is n - 1.

Proof. Denote **H** as the incidence matrix of \mathcal{G} , we can compute its Laplacian matrix $\mathbf{L} = \mathbf{I} - \mathbf{D}_v^{-\frac{1}{2}} \mathbf{H} \mathbf{W} \mathbf{D}_e^{-1} \mathbf{H}^T \mathbf{D}_v^{-\frac{1}{2}}$. For any vector $\mathbf{x} \in \mathbb{R}^n$, we have

$$\mathbf{x}^{T}\mathbf{L}\mathbf{x} = \mathbf{x}^{T}(\mathbf{I} - \mathbf{D}_{v}^{-\frac{1}{2}}\mathbf{H}\mathbf{W}\mathbf{D}_{e}^{-1}\mathbf{H}^{T}\mathbf{D}_{v}^{-\frac{1}{2}})\mathbf{x} = \mathbf{x}^{T}\mathbf{x} - \mathbf{x}^{T}\mathbf{D}_{v}^{-\frac{1}{2}}\mathbf{H}\mathbf{W}\mathbf{D}_{e}^{-1}\mathbf{H}^{T}\mathbf{D}_{v}^{-\frac{1}{2}}\mathbf{x}$$

$$= \sum_{u \in \mathcal{V}} \mathbf{x}(u)^{2} \sum_{e \in \mathcal{E}} \frac{\mathbf{W}(e)\mathbf{H}(u, e)}{\mathbf{D}_{v}(u)} \sum_{v \in \mathcal{V}} \frac{\mathbf{H}(v, e)}{\mathbf{D}_{e}(e)} - \sum_{e \in \mathcal{E}} \sum_{u, v \in \mathcal{V}} \frac{\mathbf{x}(u)\mathbf{H}(u, e)\mathbf{W}(e)\mathbf{H}(v, e)\mathbf{x}(v)}{\sqrt{\mathbf{D}_{v}(u)\mathbf{D}_{v}v}\mathbf{D}_{e}(e)}$$

$$= \frac{1}{2} \sum_{e \in \mathcal{E}} \sum_{u, v \in \mathcal{V}} \frac{\mathbf{W}(e)\mathbf{H}(u, e)\mathbf{H}(v, e)}{\mathbf{D}_{e}(e)} \left(\frac{\mathbf{x}(u)}{\sqrt{\mathbf{D}_{v}(u)}} - \frac{\mathbf{x}(v)}{\sqrt{\mathbf{D}_{v}(v)}}\right)^{2}$$
(1)

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Email addresses: zhoupeng@ahu.edu.cn (Peng Zhou), e19201043@stu.ahu.edu.cn (Xia Wang), csliangdu@gmail.com (Liang Du), xjli@ahu.edu.cn (Xuejun Li)

where the third equation is due to the definition of \mathbf{D}_v and \mathbf{D}_e and the fourth equation is due to the completing square formula.

Obviously, for any node u, if $\mathbf{x}(u) = \sqrt{\mathbf{D}_v(u)}$, we have $\mathbf{x}^T \mathbf{L} \mathbf{x} = 0$. Therefore, this \mathbf{x} is an eigenvector of \mathbf{L} whose corresponding eigenvalue is 0. Since we aim to prove that $rank(\mathbf{L}) = n - 1$, we need to prove that \mathbf{L} does not have any other eigenvector \mathbf{x}' (which is linearly independent with \mathbf{x}), whose corresponding eigenvalue is also 0.

We use the proof by contradiction. We assume that there exists such \mathbf{x}' whose corresponding eigenvalue is also 0, and \mathbf{x}' is linearly independent with \mathbf{x} , i.e., there does not exist a constant scalar t such that $\mathbf{x}' = t\mathbf{x}$. Since \mathbf{x}' 's corresponding eigenvalue is 0, we have

$$\mathbf{x}^{\prime T} \mathbf{L} \mathbf{x}^{\prime} = \frac{1}{2} \sum_{e \in \mathcal{E}} \sum_{u, v \in \mathcal{V}} \frac{\mathbf{W}(e) \mathbf{H}(u, e) \mathbf{H}(v, e)}{\mathbf{D}_{e}(e)} \left(\frac{\mathbf{x}^{\prime}(u)}{\sqrt{\mathbf{D}_{v}(u)}} - \frac{\mathbf{x}^{\prime}(v)}{\sqrt{\mathbf{D}_{v}(v)}} \right)^{2} = 0, \quad (2)$$

which means for any two nodes u and v, if there exists a hyperedge e such that $u \in e$ and $v \in e$ (i.e., $\mathbf{H}(u, e) = \mathbf{H}(v, e) = 1$), then $\frac{\mathbf{x}'(u)}{\sqrt{\mathbf{D}_v(u)}} = \frac{\mathbf{x}'(v)}{\sqrt{\mathbf{D}_v(v)}}$. Since \mathcal{G} is a connective hypergraph, which means for any two nodes u and v, there

exists at least one path e_1, \dots, e_r such that $u \in e_1, u_1 \in e_1, u_1 \in e_2, u_2 \in e_2, u_2 \in e_3, \dots, u_r \in e_r$, and $v \in e_r$. Then, we have $\frac{\mathbf{x}'(u)}{\sqrt{\mathbf{D}_v(u)}} = \frac{\mathbf{x}'(u_1)}{\sqrt{\mathbf{D}_v(u_1)}} = \dots = \frac{\mathbf{x}'(v)}{\sqrt{\mathbf{D}_v(v)}}$. Therefore, $\mathbf{x}' = t\sqrt{diag(\mathbf{D}_v)} = t\mathbf{x}$, which is contradict with the assumption that \mathbf{x}' is linearly independent with \mathbf{x} . This concludes the proof of Lemma 1.

Now come back to the proof of Theorem 1. Suppose \mathcal{G} has c' connective components $\mathcal{G}_1, \dots, \mathcal{G}_{c'}$. It is easy to verify that the incidence matrix \mathbf{Y} of \mathcal{G} can be written as the direct sum of incidence matrices $\mathbf{Y}_1, \dots, \mathbf{Y}_{c'}$ of $\mathcal{G}_1, \dots, \mathcal{G}_{c'}$, i.e., $\mathbf{Y} = \mathbf{Y}_1 \oplus \dots \oplus \mathbf{Y}_{c'}$ where \oplus denotes the direct sum. Then the Laplacian matrix \mathbf{L} can also be written as the direct sum of $\mathbf{L}_1, \dots, \mathbf{L}_{c'}$. Therefore, we have

$$rank(\mathbf{L}) = rank(\mathbf{L}_1 \oplus \cdots \oplus \mathbf{L}_{c'}) = \sum_{p=1}^{c'} rank(\mathbf{L}_p).$$
(3)

According to Lemma 1, for \mathcal{G}_p which has n_p instances, we have $rank(\mathbf{L}_p) = n_p - 1$.

Then

$$rank(\mathbf{L}) = \sum_{p=1}^{c'} rank(\mathbf{L}_p) = \sum_{p=1}^{c'} n_p - c' = n - c'.$$
(4)

Note that $rank(\mathbf{L}) = n - c$, we have c' = c, i.e., \mathcal{G} has c connective components, ²⁵ which concludes the proof of Theorem 1.