

# Applied spectral graph analysis—Solutions

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## 1 What is an irreducible matrix?

**Theorem 1.1.** *A matrix  $A$  is irreducible if and only if  $\mathcal{G}(A)$  is strongly connected.*

PROOF. Suppose that  $A$  is reducible. Apart of a permutation, we can assume that  $A$  is already in reduced block form:

$$A = \begin{pmatrix} A_{11} & A_{12} \\ O & A_{22} \end{pmatrix}, \quad A_{11} \in \mathbb{R}^{n_1 \times n_1}, \quad A_{22} \in \mathbb{R}^{n_2 \times n_2}, \quad (1)$$

with  $n_1 + n_2 = n$ . Hence, in  $\mathcal{G}(A)$  there are no edges connecting the nodes  $n_1 + 1, \dots, n$  with the nodes  $1, \dots, n_1$ . As a consequence, there are no walks going from nodes  $n_1 + 1, \dots, n$  to nodes  $1, \dots, n_1$ , and the graph is not strongly connected.

Conversely, if  $\mathcal{G}(A)$  is not strongly connected then there are two distinct nodes, say  $i$  and  $j$ , such that there is no walk from  $i$  to  $j$ . Let  $\mathcal{I}$  be the set of all nodes that can be reached by a walk starting from  $i$ , and let  $\mathcal{J}$  be its complementary set. Note that  $i \in \mathcal{I}$  and  $j \in \mathcal{J}$ . By renumbering nodes, we can suppose that  $\mathcal{I} = \{n_1 + 1, \dots, n\}$  and  $\mathcal{J} = \{1, \dots, n_1\}$ . Observe that there are no edges from nodes in  $\mathcal{I}$  to nodes in  $\mathcal{J}$ . Hence  $A$  has the form (1), that is,  $A$  is reducible. ■

## 2 A closeness centrality index

Let  $\mathcal{G}$  be a graph and let  $L$  be its Laplacian matrix. The *resistance distance* between nodes  $i$  and  $j$  is given by

$$R(i, j) = (e_i - e_j)^T L^+ (e_i - e_j).$$

Define the *current-flow closeness centrality* of node  $i$  as

$$C(i) = \frac{1}{n} \sum_{j=1}^n R(i, j).$$

1. Prove that the resistance distance is really a distance.

*Answer: The identity  $R(i, j) = R(j, i)$  is trivial. The inequality  $R(i, j) \geq 0$  follows from positive semidefiniteness of  $L^+$ . Moreover,*

$$R(i, j) = 0 \iff e_i - e_j \in \text{Ker}(L^+) \iff e_i = e_j \iff i = j.$$

*In order to prove the triangle inequality, consider the following preliminary result:*

**Lemma 2.1.** *For all  $i, j, k$  we have*

$$e_j^T L^+ (e_i - e_j) \leq e_k^T L^+ (e_i - e_j) \leq e_i^T L^+ (e_i - e_j).$$

PROOF. Suppose  $i \neq j$ , otherwise the claim is trivial. For notational simplicity, let  $v = L^+(e_i - e_j)$ . From the relation  $Lv = e_i - e_j$  we deduce that  $v$  is not constant, otherwise we have  $e_i - e_j = Lv = 0$ . Let  $M$  be the maximum value of  $v$ . Then, there exist two distinct nodes  $p$  and  $q$  such that  $v_p = M$ ,  $v_q < M$  and moreover  $p \sim q$  (otherwise either  $v$  is constant or  $\mathcal{G}$  is not connected). If  $p \neq i$  then, by looking at the  $p$ -th equation of  $Lv = e_i - e_j$  we have

$$\text{deg}(p)v_p - \sum_{\ell: \ell \sim p} v_\ell \leq 0 \quad \rightsquigarrow \quad M \leq \frac{1}{\text{deg}(p)} \sum_{\ell: \ell \sim p} v_\ell < M.$$

Indeed, all terms in the last sum are not larger than  $M$  and at least one of them (that is  $v_q$ ) is strictly smaller than  $M$ . Then  $p = i$ . From  $v_k \leq v_i$  we have  $e_k^T L^+(e_i - e_j) = v_k \leq v_i = e_i^T L^+(e_i - e_j)$  for  $k = 1, \dots, n$ . The other inequality is shown analogously, by arguing on the minimum of  $v$ . ■

With the help of the previous lemma we obtain, for any  $i, j, k$ ,

$$\begin{aligned} R(i, j) + R(j, k) &= (e_i - e_j)^T L^+(e_i - e_j) + (e_j - e_k)^T L^+(e_j - e_k) \\ &\geq (e_i - e_k)^T L^+(e_i - e_j) + (e_i - e_k)^T L^+(e_j - e_k) \\ &= (e_i - e_k)^T L^+(e_i - e_k) = R(i, k), \end{aligned}$$

and the proof is complete.

2. Prove that

$$C(i) = (L^+)_{ii} + \frac{1}{n} \text{trace}(L^+).$$

Answer: by denoting  $e = (1, \dots, 1)^T$  we have

$$\begin{aligned} C(i) &= \frac{1}{n} \sum_{j=1}^n (e_i - e_j)^T L^+(e_i - e_j) = \frac{1}{n} \sum_{j=1}^n [(L^+)_{ii} - 2e_i^T L^+ e_j + (L^+)_{jj}] \\ &= (L^+)_{ii} - \frac{2}{n} \underbrace{e_i^T L^+ e}_{=0} + \frac{1}{n} \sum_{j=1}^n (L^+)_{jj} \\ &= (L^+)_{ii} + \frac{1}{n} \text{trace}(L^+). \end{aligned}$$

Indeed  $\text{Ker}(L) = \text{Ker}(L^+)$ , whence  $L^+ e = 0$ .

**Remark 2.2.** It is not difficult to see that the function  $\|v\|_* = \sqrt{v^T L^+ v}$  is a norm on the orthogonal complement of  $\text{Ker}(L^+)$ , that is, the set  $\{v : e^T v = 0\}$ . Hence, if we could define  $R(i, j) = \|e_i - e_j\|_*$  then the first part of the exercise becomes immediate. Unfortunately this is not the case, because of the square root. The resistance distance has been introduced in the paper

D. J. KLEIN, M. RANDIĆ. Resistance distance. J. of Mathematical Chemistry, 12 (1993), 81–95.

In that paper (which is freely available on the Internet) the authors prove that  $R(i, j)$  is a distance function by using a very brief argument which exploits the electric circuit analogy.

### 3 HITS scores on a modified network

Suppose that in the digraph  $\mathcal{G}$  node  $j$  has no inlinks ( $\text{deg}^-(j) = 0$ ). Let  $i$  ( $i \neq j$ ) be a node having positive hub score ( $h_i > 0$ ). We modify  $\mathcal{G}$  by adding the oriented edge  $(i, j)$ . Prove the strict inequality

$$\forall \ell \neq i, \quad \frac{\bar{h}_\ell}{h_\ell} < \frac{\bar{h}_i}{h_i},$$

where  $\bar{h}_i$  is the updated hub score of node  $i$ , which shows that, for any fixed normalization, the hub score of node  $i$  gets the largest relative increase.

Answer: Let  $H$  and  $\bar{H}$  denote the hub matrix before and after the addition of the new edge. Owing to the hypotheses, simple computations show that


$$\bar{H} = H + e_i e_i^T.$$

Recall that a hub matrix is nonnegative, symmetric, and positive semidefinite. Hence  $\rho(H) = \lambda_{\max}(H)$ , the hub vector being an associated eigenvector. As a consequence,

$$\rho(\bar{H}) = \sup_{v \neq 0} \frac{v^T \bar{H} v}{v^T v} \geq \frac{h^T \bar{H} h}{h^T h} = \frac{h^T (H + e_i e_i^T) h}{h^T h} = \frac{h^T H h + h_i^2}{h^T h} > \frac{h^T H h}{h^T h} = \rho(H).$$


Hence  $\rho(\bar{H}) > \rho(H)$ . The claim follows immediately from Dietzenbacher's theorem.

**Remark 3.1.** The following example shows that the hypothesis  $h_i > 0$  is necessary to conclude that  $\rho(\bar{H}) > \rho(H)$ :



$$A = \begin{pmatrix} 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad H = AA^T = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

Hence  $\rho(H) = 2$  and  $h = (1, 0, 0)^T$ . Note that HITS behaves fairly on this graph. Adding the edge  $(2, 1)$  we have



$$\bar{A} = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \bar{H} = \bar{A}\bar{A}^T = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}.$$

Hence  $\rho(\bar{H}) = 2$  and  $\bar{h} = (1, 0, 0)^T$ . Thus, any solution of this exercise that does not exploit the assumption  $h_i > 0$  is not entirely correct.

## 4 A workload balancing process

To every node of a graph we allocate an initial workload  $x_i(0) \in \mathbb{R}$ ,  $i = 1, \dots, n$ . The workload is then updated at discrete time instants according to the following rule: At every time step, every node sends a fixed fraction  $0 < \alpha < 1$  of its current workload to its neighbors (and receives their workload fractions):

$$x_i(t+1) = x_i(t) + \alpha \sum_{j:i \sim j} (x_j(t) - x_i(t)).$$

1. Prove that  $\sum_{i=1}^n x_i(t)$  is constant over time.

*Answer:* Firstly, observe that the vector  $x(t) = (x_1(t), \dots, x_n(t))^T$  fulfills

$$x(t+1) = x(t) - \alpha Lx(t). \quad (2)$$

Now, recalling that  $L$  is symmetric and  $Le = 0$  we obtain

$$\sum_{i=1}^n x_i(t+1) = e^T x(t+1) = e^T x(t) - \alpha \underbrace{e^T L}_{=0} x(t) = e^T x(t) = \sum_{i=1}^n x_i(t).$$

2. Describe the stationary workload distributions.

*Answer:* we have  $x(t+1) = x(t) \Leftrightarrow Lx(t) = 0 \Leftrightarrow x(t) \in \text{Ker}(L)$ . The latter holds if and only if  $x(t)$  is a multiple of  $e = (1, \dots, 1)^T$ , the uniform workload.

3. Find a necessary and sufficient condition (in terms of the Laplacian spectrum) so that any initial workload distribution evolves toward a stationary distribution.

*Answer:* The recurrence (2) is exactly the power method applied to the matrix  $I - \alpha L$ . The sought condition is then equivalent to the requirement that  $1 = \lambda_1(I - \alpha L)$  is a dominant eigenvalue, that is,  $-1 < \lambda_i(I - \alpha L) < 1$  for  $i = 2, \dots, n$ . The latter is equivalent to the condition  $0 < \lambda_i(L) < 2/\alpha$  for  $i = 2, \dots, n$ , that is, the graph is connected and  $\rho(L) < 2/\alpha$ .

**Remark 4.1.** In the third part of this exercise, the inequality  $\rho(I - \alpha L) < 1$  implies  $x(t) \rightarrow 0$  as  $t \rightarrow \infty$ , which is not the desired behavior.