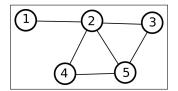
Graph Signal Processing - Graph Laplacian

Prof. Luis Gustavo Nonato

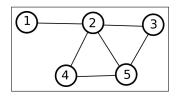
August 23, 2017

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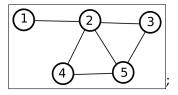


$$L = D - A$$

A is the adjacency matrix and **D** is a diagonal matrix with $d_{ii} = \sum_{i} a_{ij}$

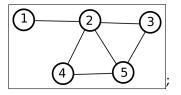
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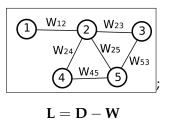
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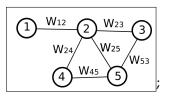
$$\underbrace{ \begin{bmatrix} 1 & -1 & 0 & 0 & 0 \\ -1 & 4 & -1 & -1 & -1 \\ 0 & -1 & 2 & 0 & -1 \\ 0 & -1 & 0 & 2 & -1 \\ 0 & -1 & -1 & -1 & 3 \end{bmatrix} }_{\mathbf{L}} = \underbrace{ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix} }_{\mathbf{D}} - \underbrace{ \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix} }_{\mathbf{A}}$$

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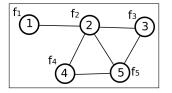


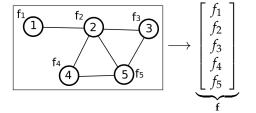
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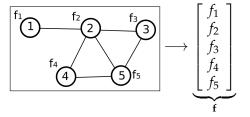


$$L = D - W$$

$$\left[\begin{array}{ccccc} w_{12} & -w_{12} & 0 & 0 & 0 \\ -w_{21} & \sum_{j \neq 2} w_{2j} & -w_{23} & -w_{24} & -w_{25} \\ 0 & -w_{32} & \sum_{j \neq 3} w_{3j} & 0 & -w_{35} \\ 0 & -w_{42} & 0 & \sum_{j \neq 4} w_{4j} & -w_{45} \\ 0 & -w_{52} & -w_{53} & -w_{54} & \sum_{j \neq 5} w_{5j} \end{array} \right]$$

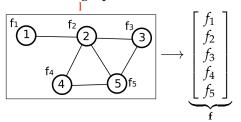






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or equivalently

$$f_i = \frac{1}{l_{ii}} \sum_{i \neq i} f_j$$

(the value in each node is the average of values in neighbor nodes)

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■ The eigenvectors are "nice" functions defined on the graph.

Property 1

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$$\mathbf{L}\mathbf{u}_{0} = \begin{bmatrix} \vdots \\ -w_{i1} & 0 & -w_{i3} & \cdots & \sum_{j} w_{ij} & \cdots & 0 & -w_{3(n-1)} & 0 \end{bmatrix} \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} = 0\mathbf{u}_{0}$$

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Imposing the additional constraint $\|\mathbf{f}\|^2 = 1$, the Courant-Fiecher theorem ensures that the minimum is reached when \mathbf{f} is the eigenvector associated to the second smallest eigenvalue.

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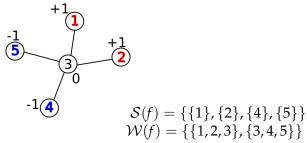
$$\mathbf{F} = \left[egin{array}{cccc} ert & ert & ert \ \mathbf{u}_1 & \mathbf{u}_2 & \cdots & \mathbf{u}_d \ ert & ert & ert \end{array}
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where \mathbf{u}_i are the eigenvectors of \mathbf{L} .

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Property 4: Discrete Courant's Nodal Theorem

Let G be a connected graph with n vertices. Any Graph Laplacian eigenvector \mathbf{u}_k with corresponding eigenvalue λ_k with multiplicity r has at most k+1 weak nodal domains and k+r strong nodal domains, i.e.,

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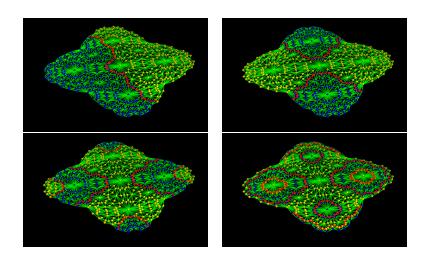
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This theorem was proved by Davies, Gladwell, Leydold, Stadler in 2001 and it is the discrete version of the Courant's Nodal Theorem for the Laplace operator on manifolds.



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- Normalized Graph Laplacian is also closely related with random walks on graphs.

$$\mathbf{P} = \mathbf{D}^{-1/2} (\mathbf{I} - \mathcal{L}) \mathbf{D}^{1/2}$$