

Graphs in Machine Learning

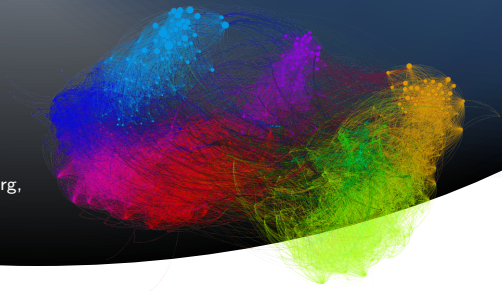
Normalized Laplacians

L_{sym} and L_{rw}

Michal Valko

Inria & ENS Paris-Saclay, MVA

Partially based on material by: Ulrike von Luxburg,
Miller, Doyle & Schnell, Daniel Spielman



Smoothness of the Function and Laplacian

$$S_G(\mathbf{f}) = \mathbf{f}^\top \mathbf{L} \mathbf{f} = \mathbf{f}^\top \mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^\top \mathbf{f} = \boldsymbol{\alpha}^\top \mathbf{\Lambda} \boldsymbol{\alpha} = \|\boldsymbol{\alpha}\|_{\mathbf{\Lambda}}^2 = \sum_{i=1}^N \lambda_i \alpha_i^2$$

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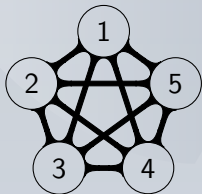
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The smoothness of k -th eigenvector is the k -th eigenvalue.

Laplacian of the Complete Graph K_N

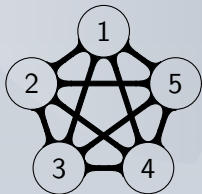
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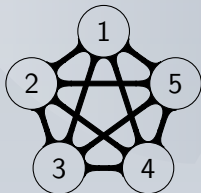
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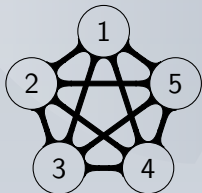
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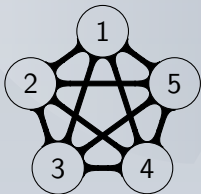
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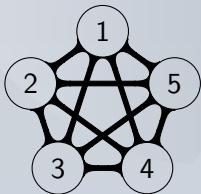
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Answer: $N-1$ eigenvectors $\perp \mathbf{1}_N$ for eigenvalue N with multiplicity $N-1$.

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(λ, \mathbf{u}) is an eigenpair for \mathbf{L}_{rw} iff $(\lambda, \mathbf{D}^{1/2} \mathbf{u})$ is an eigenpair for \mathbf{L}_{sym}



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<https://misovalko.github.io/mva-ml-graphs.html>