

Sparse Eigenvectors of Graphs

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42nd International Conference on
Acoustics, Speech and Signal Processing

Caltech

Outline

- 1 Graph Signal Processing
- 2 Motivation
- 3 Sparse Eigenvectors of Graphs
 - Disconnected Graphs
 - Connected Graphs
 - Generalizations
- 4 Real-World Examples
- 5 Conclusions

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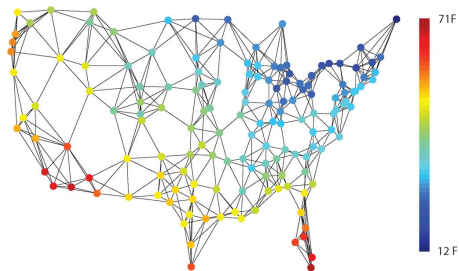
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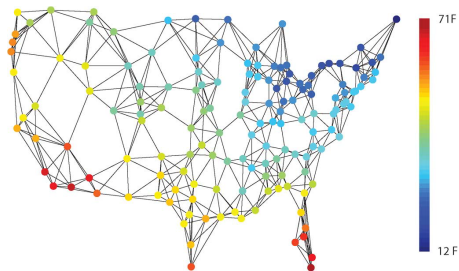
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Preliminaries



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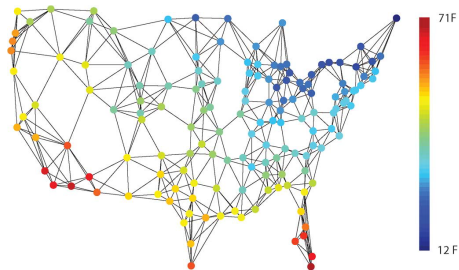
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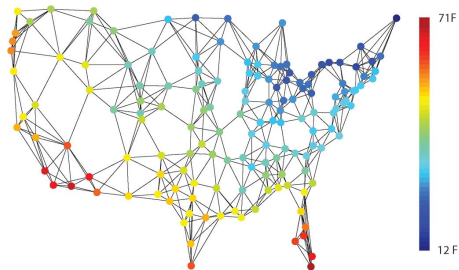
Adjacency matrix ¹	:	\mathbf{A}
Graph Laplacians ²	:	\mathbf{L} , or \mathcal{L}
Other selections ³		

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² Shuman et al, "The emerging field of signal processing on graphs: ...," *IEEE S. P. Magazine*, vol. 30, no. 3 2013

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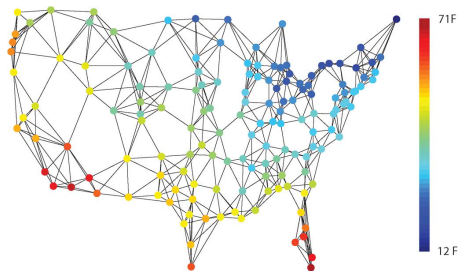
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Graph Fourier Basis : V
 Graph Fourier Transform : $F = V^{-1}$

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$$\mathbf{F}^{-1} = \mathbf{V} = [\mathbf{v}_1 \ \mathbf{v}_2 \ \cdots \ \mathbf{v}_N] \qquad s_0(\mathbf{v}_i) = \frac{\|\mathbf{v}_i\|_0 + 1}{2}$$

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Sparse eigenvectors in *connected* graphs.

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Connected graph \implies No 1-sparse eigenvector!

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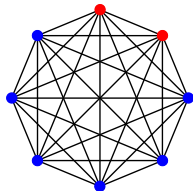
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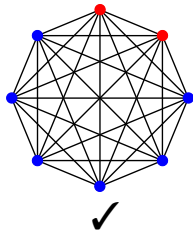
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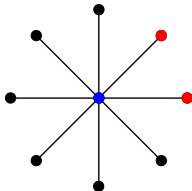
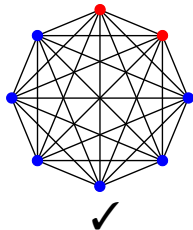
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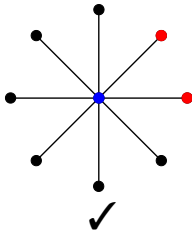
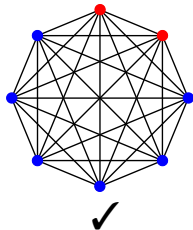
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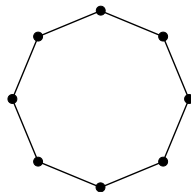
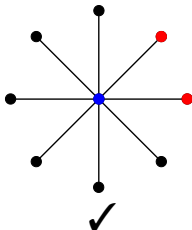
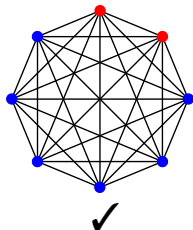
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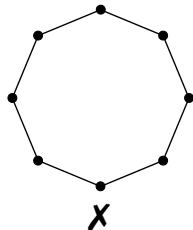
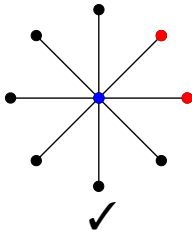
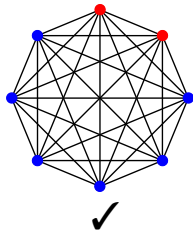
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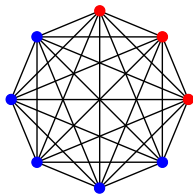
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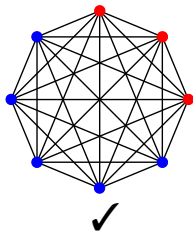


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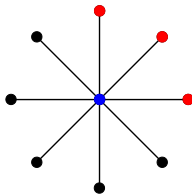
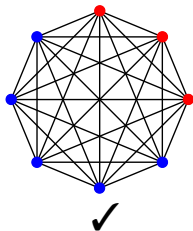


3-sparse Case

Theorem (3-sparse eigenvectors)

Assume the graph is *unweighted*, *undirected* and *connected*.
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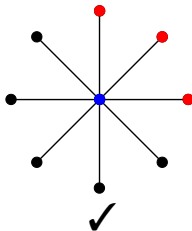
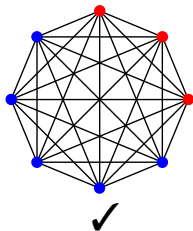


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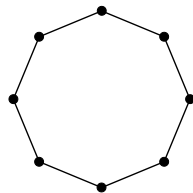
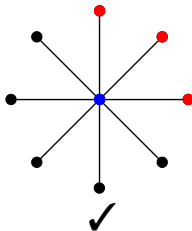
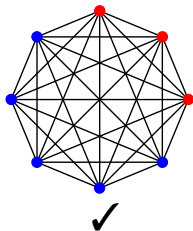


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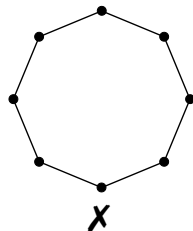
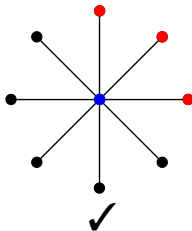
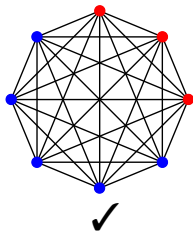


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K -Sparse Case

Can we generalize to arbitrary K ?

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1-sparse eigenvector



$$\mathcal{N}(i) = \{\}$$

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1-sparse eigenvector \iff

$$\mathcal{N}(i) = \{\}$$

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$$\mathcal{N}(i) \setminus \{j\} = \mathcal{N}(j) \setminus \{i\}$$

K -Sparse Case

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- 1-sparse eigenvector $\iff \mathcal{N}(i) = \{\}$
- 2-sparse eigenvector $\iff \mathcal{N}(i) \setminus \{j\} = \mathcal{N}(j) \setminus \{i\}$
- 3-sparse eigenvector $\iff \mathcal{N}(i) \setminus \{j, k\} = \mathcal{N}(j) \setminus \{i, k\} = \mathcal{N}(k) \setminus \{i, j\}$

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K -nodes such that neighbors (except from each other) are the same.



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There is a K -sparse eigenvector.

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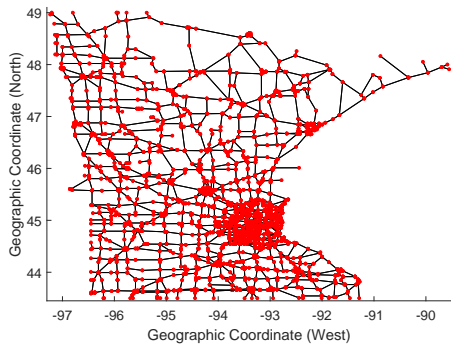
This is only sufficient, but not necessary.

(Counter-examples to follow)

Outline

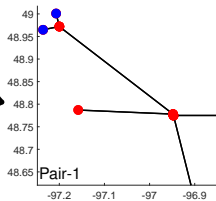
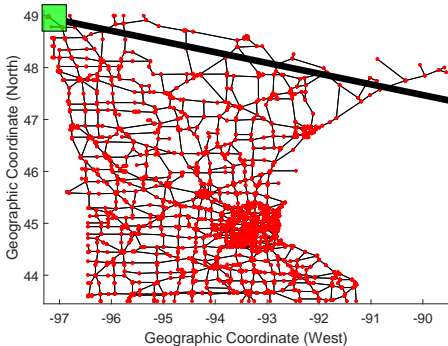
- 1 Graph Signal Processing
- 2 Motivation
- 3 Sparse Eigenvectors of Graphs
 - Disconnected Graphs
 - Connected Graphs
 - Generalizations
- 4 Real-World Examples**
- 5 Conclusions

Minnesota Road Graph



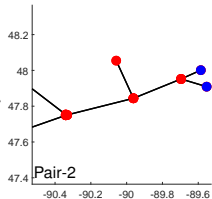
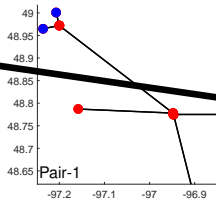
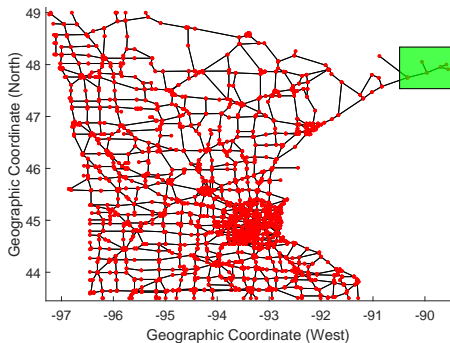
Minnesota Road Graph

2-Sparse Case: $\mathcal{N}(i) \setminus \{j\} = \mathcal{N}(j) \setminus \{i\}$



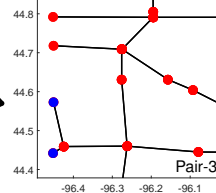
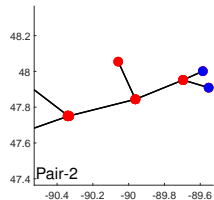
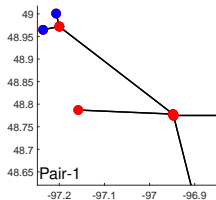
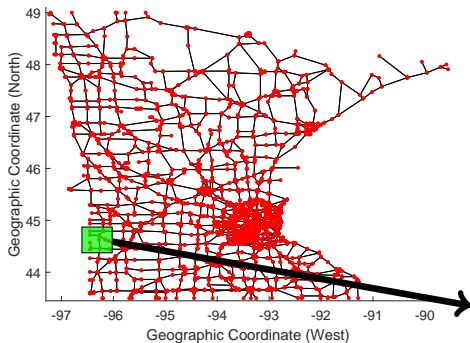
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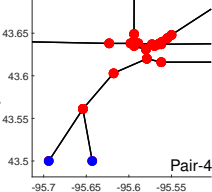
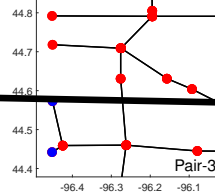
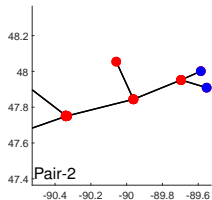
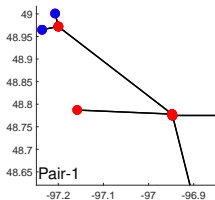
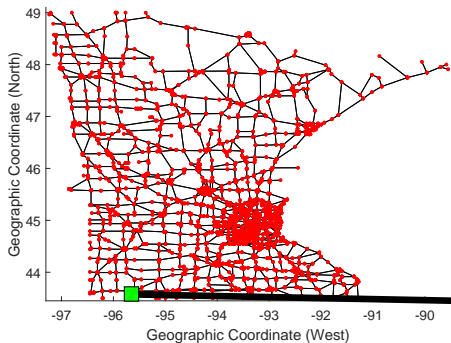
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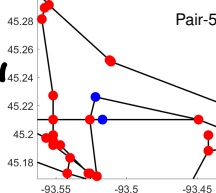
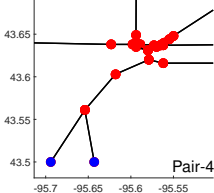
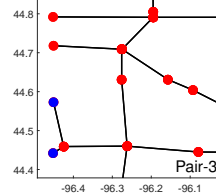
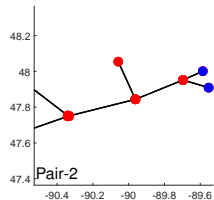
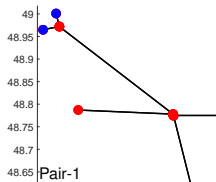
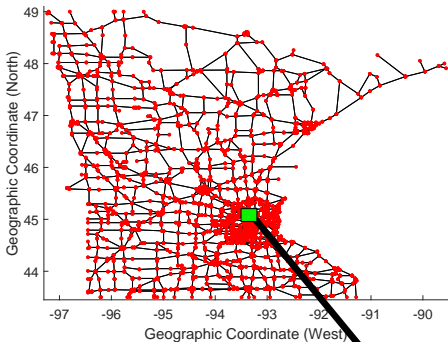
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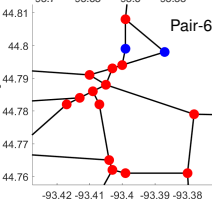
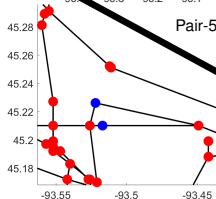
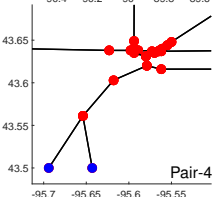
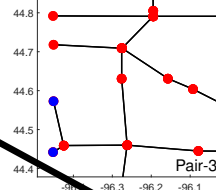
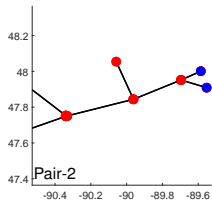
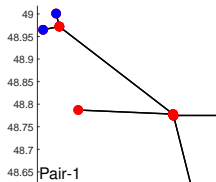
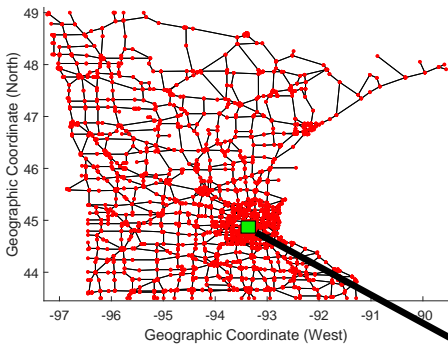


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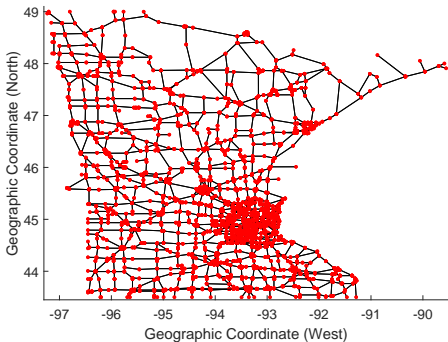


Minnesota Road Graph

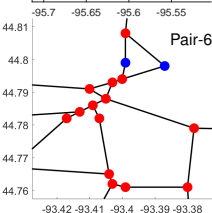
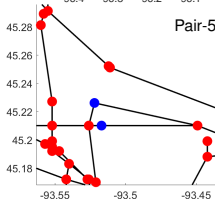
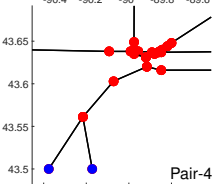
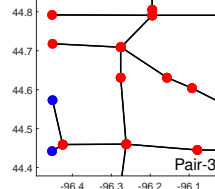
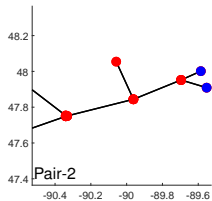
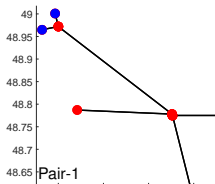
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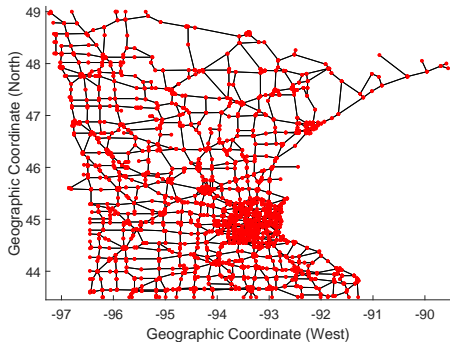


Pairs 1 - 4 have $\lambda = 1$



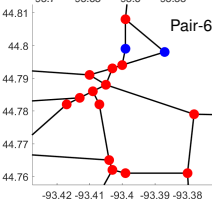
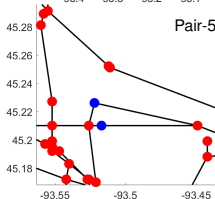
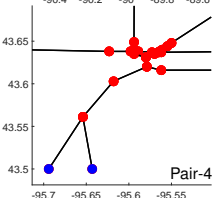
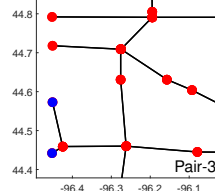
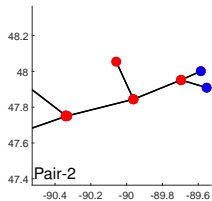
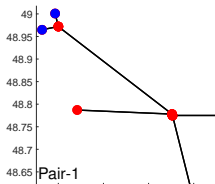
Minnesota Road Graph

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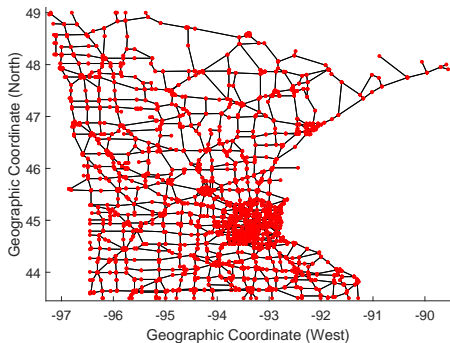
Pairs 1 - 4 have $\lambda = 1$

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Minnesota Road Graph

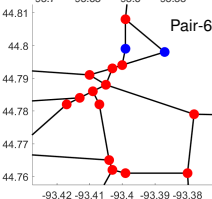
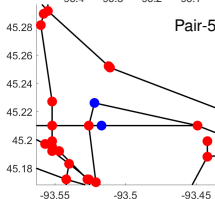
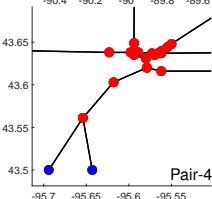
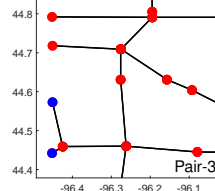
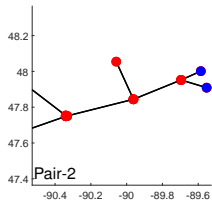
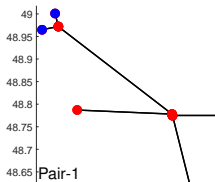
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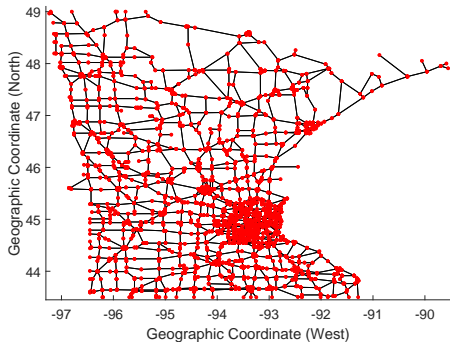
Pairs 5 - 6 have $\lambda = 2$

4, 6, 8-sparse exist as well!



Minnesota Road Graph

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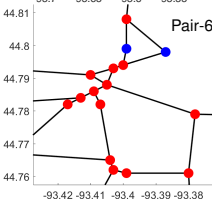
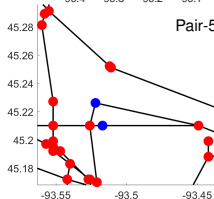
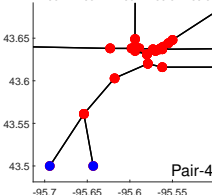
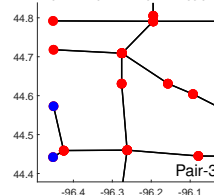
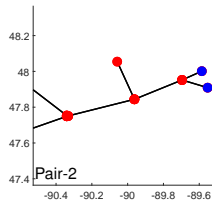
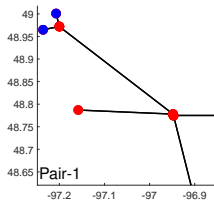


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4, 6, 8-sparse **exist** as well!

3-sparse does **not** exist!



Co-appearance Network of Novel Les Misérables

Co-appearance Network of Novel Les Misérables

Nodes = Characters
(77)

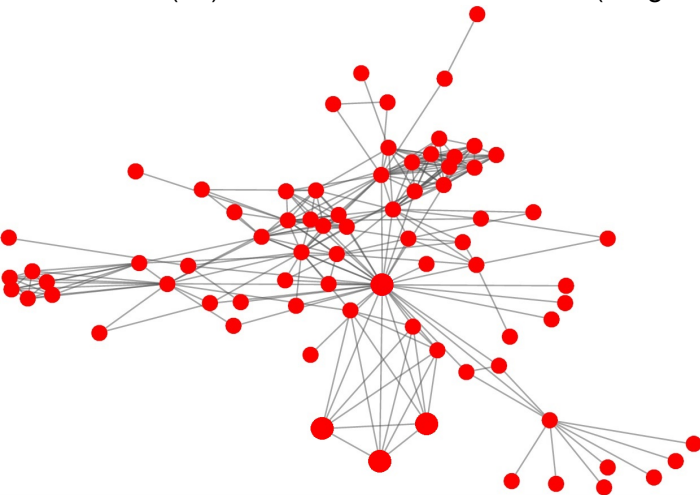
Connectivity = Co-Appearance⁷
(weighted)

⁷ M. E. J. Newman, " (2013) Network data. [Online]." Available: <http://www-personal.umich.edu/~mejn/netdata/>

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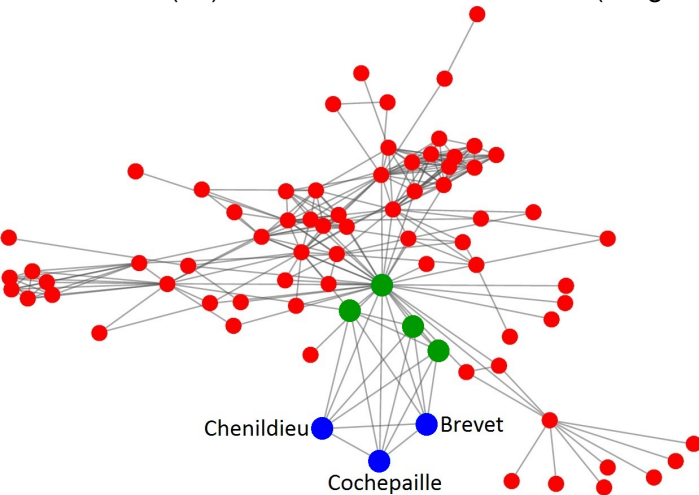


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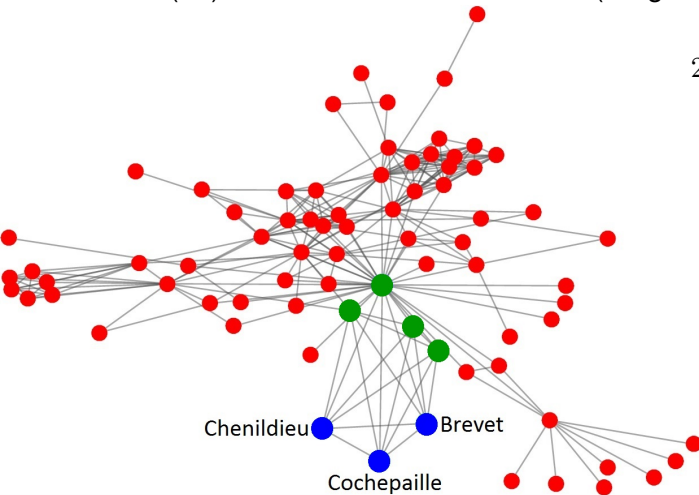
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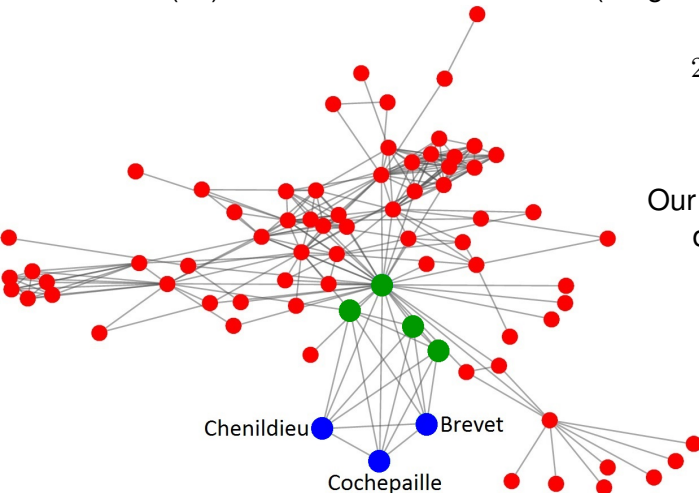


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Co-appearance Network of Novel Les Misérables

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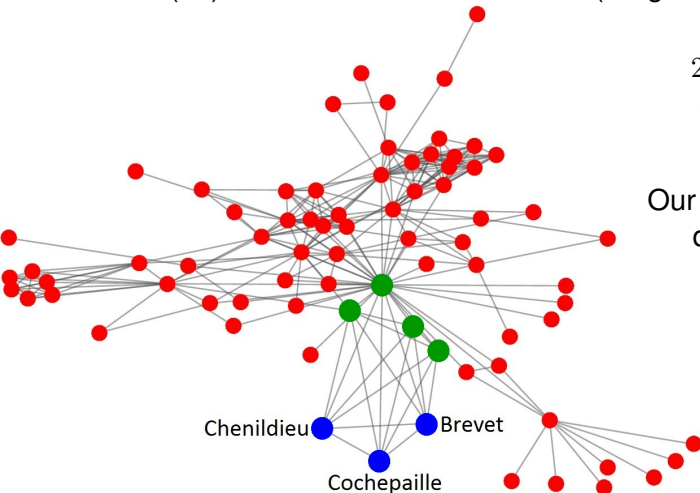
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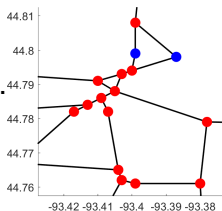
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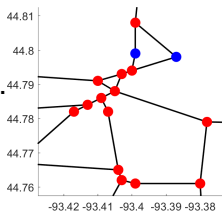
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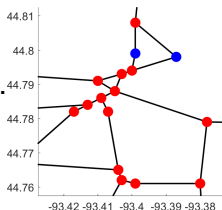
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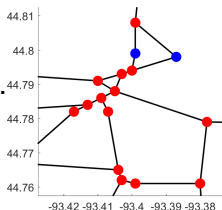
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Theorem

Assume the graph is *simple* and *connected*.
 3 -sparse eigenvector \implies 2 -sparse eigenvector.

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Outline

- 1 Graph Signal Processing
- 2 Motivation
- 3 Sparse Eigenvectors of Graphs
 - Disconnected Graphs
 - Connected Graphs
 - Generalizations
- 4 Real-World Examples
- 5 Conclusions**

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- 2 Disconnected graphs trivially have sparse eigenvectors.
- 3 Necessary&Sufficient conditions for 1, 2 and 3-sparse eigenvectors
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Thank you!