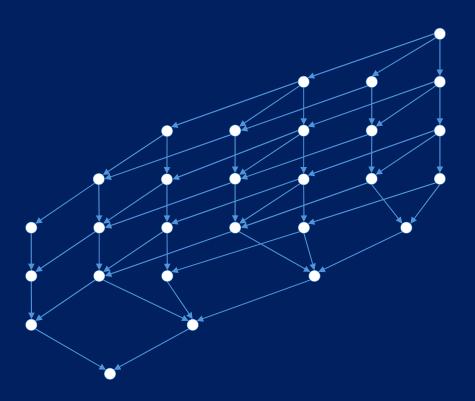
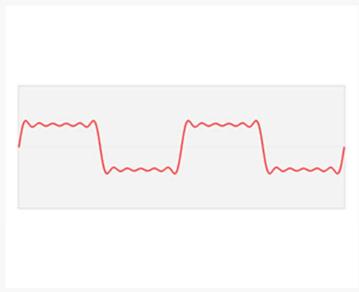
Graph Signal Processing

Bastian Seifert Sommersemester 2025



Fourier Analysis



Animation: Lucas V. Barbosa - Own work, Public Domain, https://commons.wikimedia.org/w/index.php?curid=24830373

Integrate against eigenfunctions of Laplace operator

$$\mathcal{L} = -\frac{d^2}{dx^2}$$

which are

$$e^{inx} = \cos(nx) + i\sin(nx)$$

Hearing the shape of a drum

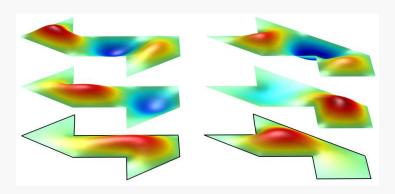


Figure: Chien Liu https://www.comsol.com/blogs/can-we-hear-the-shape-of-a-drum

Associate eigenvalues of Laplace operator

$$\Delta = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}$$

to properties of the shape

Eigenvectors and Eigenvalues

A vector ${\bf u}$ and a scalar λ are an eigenvector and and eigenvalue of the shift if

$$T\mathbf{u} = \lambda \mathbf{u}$$

Independent eigenvectors are eigenvectors which can not be written as linear combination of the others.

A matrix is diagonalizable if it has as many independent eigenvectors as its size. Then

$$T = U\Lambda U^{-1}$$

where Λ is a diagonal matrix.

Examples

Shifts of undirected graphs are diagonalizable

Diagonalizable matrices

Real symmetric matrices, i.e., ones with

$$A = A^T$$

are always diagonalizable and have only real eigenvalues.

Not every matrix is diagonalizable.

Non-symmetric diagonalizable matrices typically have pairs of complex eigenvalues.

Simultaneous diagonalization

Matrices are simulatenous diagonalizable if they can be diagonalized by the same matrix, i.e.,

$$T = U\Lambda_1 U^{-1}, H = U\Lambda_2 U^{-1}$$

If matrices commute, they preserve eigenvectors,

$$T(H\mathbf{u}) = H(T\mathbf{u}) = H(\lambda \mathbf{u}) = \lambda H\mathbf{u}$$

so they can be simultaneously diagonalized

H Sitter => P(T) = $\sum_{k=0}^{N} a_k T^k = H$ $T^k = U + V - 1 = V - 1 + V - 1 + V - 1 = V - 1 + V$

Filters and shift can be diagonalized by the same matrix

Graph Fourier transform

Eigenvalues of shift = graph frequencies, spectrum

Eigenvectors = frequency component

Graph Fourier transform of signal is

$$\hat{\mathbf{s}} = \mathcal{F}\mathbf{s}$$

with

$$\mathcal{F} = U^{-1}$$

for

$$A = U\Lambda U^{-1}$$

Frequency response

The frequency response describes the effect of a filter to the frequency content of a signal

$$\tilde{\mathbf{s}} = H(A)\mathbf{s} = \mathcal{F}^{-1}H(\Lambda)\mathcal{F}\mathbf{s}$$
 \Leftrightarrow

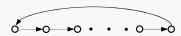
$$\mathcal{F}\tilde{\mathbf{s}} = H(\Lambda)\hat{\mathbf{s}}$$

(convolution theorem) and is defined as

$$\widehat{H(A)} = H(\Lambda)$$

Filtering a signal on a graph is equivalent to multiplying the signal spectrum with the frequency response of the filter

Cycle graph



$$A = \frac{1}{N} DFT_N^{-1} \begin{bmatrix} e^{-i \cdot \frac{2\pi \cdot 0}{N}} & & \\ & \ddots & \\ & & e^{-i \cdot \frac{2\pi \cdot (N-1)}{N}} \end{bmatrix} DFT_N$$

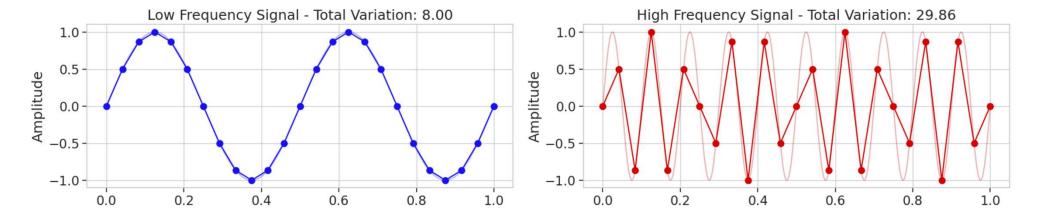
Weighted path graph

$$A = \frac{1}{N} DFT_N^{-1} \begin{bmatrix} e^{-i \cdot \frac{2\pi \cdot 0}{N}} & \\ & \ddots & \\ & & e^{-i \cdot \frac{2\pi \cdot (N-1)}{N}} \end{bmatrix} DFT_N \qquad A = \frac{1}{N} DCT_N^{-1} \begin{bmatrix} \cos(\frac{\pi \cdot 0}{N}) & \\ & \ddots & \\ & & \cos(\frac{\pi \cdot (N-1)}{N}) \end{bmatrix} DCT_N$$

The graph Fourier transform generalizes classical signal transforms

Total variation of a discrete time signal is defined as

$$TV(\mathbf{s}) = \sum_{t \in T} |s_t - s_{t-1}|$$



Higher total variation = higher frequency

Graph total variation

The total variation of a graph signal is defined as

$$TV_G(\mathbf{s}) = ||\mathbf{s} - A^{\text{norm}}\mathbf{s}||_1$$

It's important to take the normalized shift here, since otherwise don't have the proper scalation for comparision of the shifted with the original signal.

$$|1| \le -A^{Na} \le |1| - \frac{1}{N_{eV}} (S_{V} - (A \le)_{V})|$$
Graph variation
$$|A = (1, 1) - A \le |1| + \frac{1}{N_{eV}} (S_{V} - (A \le)_{V})|$$

$$|1| \le -A \le |1| - \frac{1}{N_{eV}} (S_{V} - (A \le)_{V})|$$

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$$|1| \le -A \le |1| - \frac$$

Graph frequency ordering

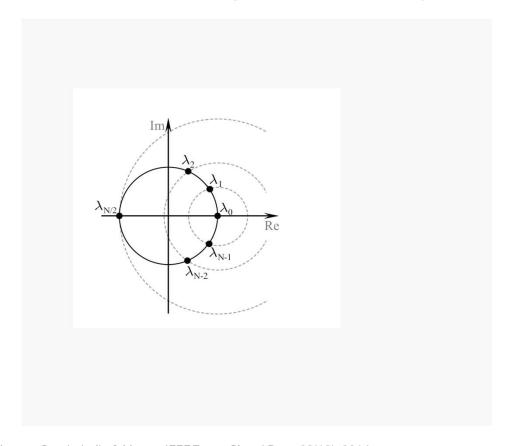
For real eigenvalues $\lambda_1 < \lambda_2$ one has

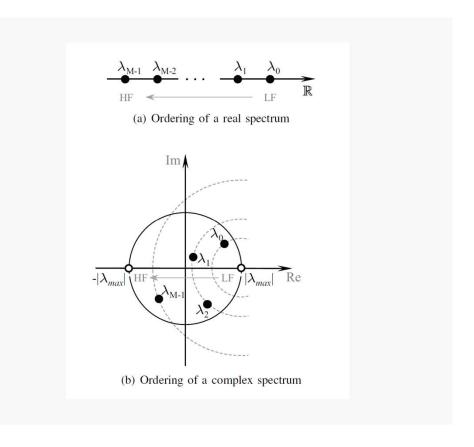
$$TV_G(u_1) > TV_G(u_2)$$

while for complex eigenvalues this is the case if if λ_1 is located nearer than λ_2 to $|\lambda_{\max}|$

Graph frequency hence are ordered by their total variations

Visualization of graph frequency ordering





Figures: Sandryhaila & Moura, IEEE Trans. Signal Proc. 62(12), 2014

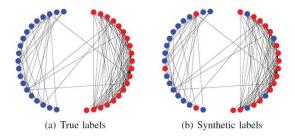


Fig. 11. A subgraph of 40 blogs labels: blue corresponds to "liberal" blogs and red corresponds to "conservative" ones. Labels in (a) form a smoother graph signal than labels in (b).

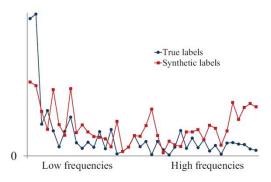


Fig. 12. Magnitudes of the spectral coefficients for graph signals formed by true and synthetic labels in Fig. $\boxed{\Pi}$

Figures: Sandryhaila & Moura, IEEE Trans. Signal Proc. 62(12), 2014

Outliers typically show by higher high frequency content