

# Fourier Analysis on Graphs

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## Primary Sources

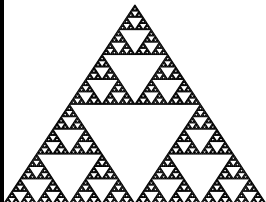
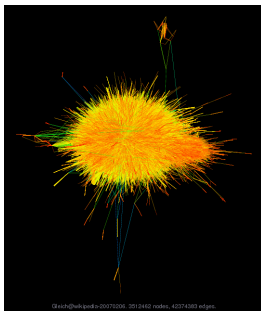
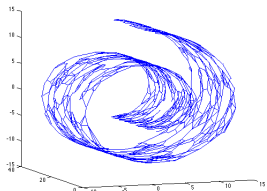
- [2] David I Shuman, Benjamin Ricaud, and Pierre Vandergheynst, *Vertex-frequency analysis on graphs*, preprint, (2013).
- [3] David K Hammond, Pierre Vandergheynst, and Rémi Gribonval *Wavelets on graphs via spectral graph theory*, Applied and Computational Harmonic Analysis **30** (2011) no. 2, 129-150.

## Secondary Sources

- [1] Fan RK Chung, *Spectral Graph Theory*, vol. 92, American Mathematical Soc., 1997.

# Why study graphs?

- Graph theory has developed into a useful tool in applied mathematics.
- Vertices correspond to different sensors, observations, or data points. Edges represent connections, similarities, or correlations among those points.



- 1 Graphs and the Graph Laplacian
- 2 Graph Fourier Transform and other Time-Frequency Operations
- 3 Windowed Graph Fourier Frames

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# Graph Preliminaries

- Denote a graph by  $G = G(V, E)$ .
- Vertex set  $V = \{x_i\}_{i=1}^N$ .  $|V| = N < \infty$ .
- Edge set,  $E$ :

$$E = \{(x, y) : x, y \in V \text{ and } x \sim y\}.$$

- We only consider *undirected graphs* in which the edge set,  $E$ , is symmetric, that is  $x \sim y \implies y \sim x$ .
- We consider a function on a graph  $G(V, E)$  to be defined on the vertex set,  $V$ . That is, we consider functions  $f : V \rightarrow \mathbb{C}$

# Graph Preliminaries, cont.

- The *degree of  $x$* , denoted  $d_x$ , to be the number of edges connected to point  $x$ .
- A graph is *connected* if for any  $x, y \in V$  There exists a sequence  $\{x_j\}_{j=1}^K \subseteq V$  such that  $x = x_0$  and  $y = x_K$  and  $(x_j, x_{j+1}) \in E$  for  $j = 0, \dots, K - 1$ .

# Laplace's operator

- In  $\mathbb{R}$ , Laplace's operator is simply the second derivative:  
We can express this with the second difference formula

$$f''(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - 2f(x) + f(x-h)}{h^2}.$$

- Suppose we discretize the real line by its dyadic points, i.e.,  $x = k/2^n$  for  $k \in \mathbb{Z}$ ,  $n \in \mathbb{N}$ .  
Each vertex has an edge connecting it to its two closest neighbors.

$$f''(x) = \lim_{n \rightarrow \infty} \frac{f(x + \frac{1}{2^n}) - 2f(x) + f(x - \frac{1}{2^n})}{(\frac{1}{2^n})^2}.$$

This is the sum of all the differences of  $f(x)$  with  $f$  evaluated at all its neighbors (and then properly renormalized).



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## Definition

The pointwise formulation for the Laplacian acting on a function  $f : V \rightarrow \mathbb{R}$  is

$$\Delta f(x) = \sum_{y \sim x} f(x) - f(y).$$

- For a finite graph, the Laplacian can be represented as a matrix. Let  $D$  denote the  $N \times N$  *degree matrix*,  $D = \text{diag}(d_x)$ . Let  $A$  denote the  $N \times N$  *adjacency matrix*,

$$A(i, j) = \begin{cases} 1, & \text{if } x_i \sim x_j \\ 0, & \text{otherwise.} \end{cases}$$

Then the unweighted graph Laplacian can be written as

$$L = D - A.$$

Equivalently,

$$L(i, j) = \begin{cases} d_{x_i} & \text{if } i = j \\ -1 & \text{if } x_i \sim x_j \\ 0 & \text{otherwise.} \end{cases}$$

$$L = D - A$$

- Matrix  $L$  is called the unweighted Laplacian to distinguish it from the renormalized Laplacian,  $\mathcal{L} = D^{-1/2}LD^{1/2}$ , used in some of the literature on graphs.
- $L$  is a symmetric matrix since both  $D$  and  $A$  are symmetric.

# Spectrum of the Laplacian

- $L$  is a real symmetric matrix and therefore has nonnegative eigenvalues  $\{\lambda_k\}_{k=0}^{N-1}$  with associated orthonormal eigenvectors  $\{\varphi_k\}_{k=0}^{N-1}$ .

- If  $G$  is finite and connected, then we have

$$0 = \lambda_0 < \lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_{N-1}.$$

- The spectrum of the Laplacian,  $\sigma(L)$ , is fixed but one's choice of eigenvectors  $\{\varphi_k\}_{k=0}^{N-1}$  can vary. Throughout the paper, we assume that the choice of eigenvectors are fixed.
- Since  $L$  is Hermitian ( $L = L^*$ ), then we can choose the eigenbasis  $\{\varphi_k\}_{k=0}^{N-1}$  to be entirely real-valued.
- Let  $\Phi$  denote the  $N \times N$  matrix where the  $k$ th column is precisely the vector  $\varphi_k$ .
- Easy to show that  $\varphi_0 \equiv 1/\sqrt{N}$ .

# Data Sets - Minnesota Road Network

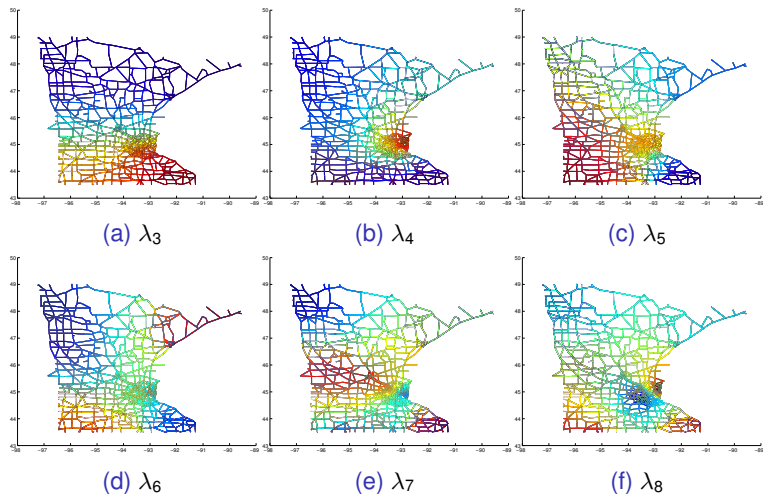


Figure : Eigenfunctions corresponding to the first six nonzero eigenvalues.  
Minnesota road graph (2642 vertices)

# Data Sets - Sierpinski gasket graph approximation

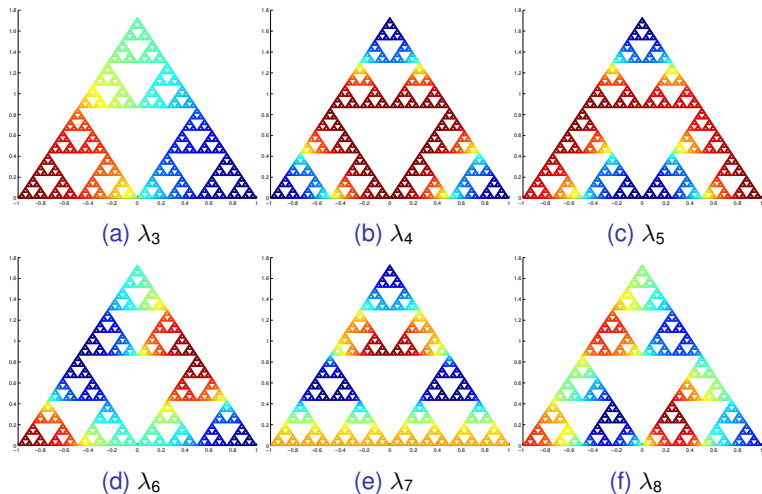
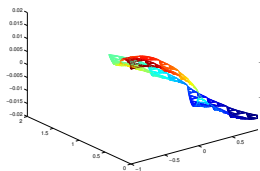
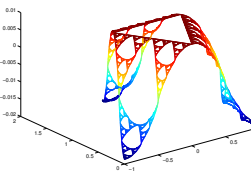


Figure : Eigenfunctions corresponding to the first six nonzero eigenvalues. Level-8 graph approximation to Sierpinski gasket (9843 vertices)

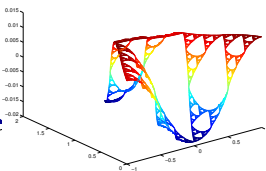
# Data Sets - Sierpinski gasket graph approximation



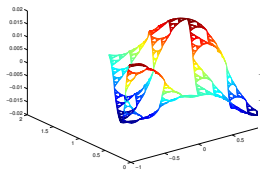
(a)  $\lambda_3$



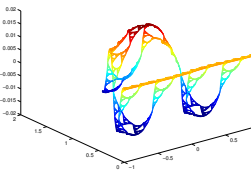
(b)  $\lambda_4$



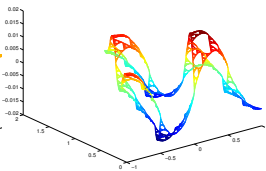
(c)  $\lambda_5$



(d)  $\lambda_6$



(e)  $\lambda_7$



(f)  $\lambda_8$

Figure : Eigenfunctions corresponding to the first six nonzero eigenvalues.  
Level-8 graph approximation to Sierpinski gasket (9843 vertices)

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- In the classical setting, the Fourier transform on  $\mathbb{R}$  is given by

$$\hat{f}(\xi) = \int_{\mathbb{R}} f(t) e^{-2\pi i \xi t} dt = \langle f, e^{2\pi i \xi t} \rangle.$$

This is precisely the expansion of  $f$  in terms of the eigenvalues of the eigenfunctions of the Laplace operator.

- Analogously, we define the *graph Fourier transform* of a function,  $f : V \rightarrow \mathbb{R}$ , as the expansion of  $f$  in terms of the eigenfunctions of the graph Laplacian.

# Graph Fourier Transform

## Definition

The *graph Fourier transform* is defined as

$$\hat{f}(\lambda_l) = \langle f, \varphi_l \rangle = \sum_{n=1}^N f(n) \varphi_l^*(n).$$

Notice that the graph Fourier transform is only defined on values of  $\sigma(L)$ .

The *inverse Fourier transform* is then given by

$$f(n) = \sum_{l=0}^{N-1} \hat{f}(\lambda_l) \varphi_l(n).$$

If we think of  $f$  and  $\hat{f}$  as  $N \times 1$  vectors, we then these definitions become

$$\hat{f} = \Phi^* f, \quad f = \Phi \hat{f}.$$

# Parseval's Identity

With this definition one can show that Parseval's identity holds. That is for any  $f, g : V \rightarrow \mathbb{R}$  we have

$$\langle f, g \rangle = \langle \hat{f}, \hat{g} \rangle.$$

**Proof.**

This can be seen easily using the matrix notation since  $\Phi$  is an orthonormal matrix. That is,

$$\langle \hat{f}, \hat{g} \rangle = \hat{f}^* \hat{g} = (\Phi^* f)^* \Phi^* g = f^* \Phi \Phi^* g = f^* g = \langle f, g \rangle.$$



This immediately gives us Plancherel's identity:

$$\|f\|_{\ell^2}^2 = \sum_{n=1}^N |f(n)|^2 = \sum_{l=0}^{N-1} |\hat{f}(\lambda_l)|^2 = \|\hat{f}\|_{\ell^2}^2.$$

- In Euclidean setting, modulation is multiplication of a Laplacian eigenfunction.

## Definition

For any  $k = 0, 1, \dots, N - 1$  the *graph modulation operator*  $M_k$ , is defined as

$$(M_k f)(n) = \sqrt{N} f(n) \varphi_k(n).$$

- Notice that since  $\varphi_0 \equiv \frac{1}{\sqrt{N}}$  then  $M_0$  is the identity operator.
- On  $\mathbb{R}$ , modulation in the time domain = translation in the frequency domain,

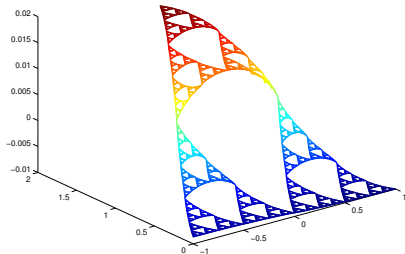
$$\widehat{M_\xi f}(\omega) = \hat{f}(\omega - \xi).$$

The graph modulation does *not* exhibit this property due to the discrete nature of the spectral domain.

# Example - Movie

$$G = SG_6$$

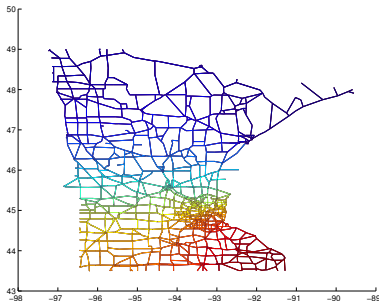
$$\hat{f}(\lambda_l) = \delta_2(l) \implies f = \varphi_2.$$



# Example - Movie

$G = \text{Minnesota}$

$$\hat{f}(\lambda_l) = \delta_2(l) \implies f = \varphi_2.$$



# Graph Convolution - Motivation and Definition

- Classically, for signals  $f, g \in L^2(\mathbb{R})$  we define the convolution as

$$f * g(t) = \int_{\mathbb{R}} f(u)g(t - u) du.$$

- However, there is no clear analogue of translation in the graph setting. So we exploit the property

$$(\widehat{f * g})(\xi) = \hat{f}(\xi)\hat{g}(\xi),$$

and then take inverse Fourier transform.

## Definition

For  $f, g : V \rightarrow \mathbb{R}$ , we define the *graph convolution* of  $f$  and  $g$  as

$$f * g(n) = \sum_{l=0}^{N-1} \hat{f}(\lambda_l)\hat{g}(\lambda_l)\varphi_l(n).$$

# Properties of graph convolution

$$f * g(n) = \sum_{l=0}^{N-1} \hat{f}(\lambda_l) \hat{g}(\lambda_l) \varphi_l(n).$$

## Proposition

For  $\alpha \in \mathbb{R}$ , and  $f, g, h : V \rightarrow \mathbb{R}$  then the graph convolution defined above satisfies the following properties:

- 1  $\widehat{f * g} = \hat{f} \hat{g}$ .
- 2  $\alpha(f * g) = (\alpha f) * g = f * (\alpha g)$ .
- 3 *Commutativity:*  $f * g = g * f$ .
- 4 *Distributivity:*  $f * (g + h) = f * g + f * h$ .
- 5 *Associativity:*  $(f * g) * h = f * (g * h)$ .



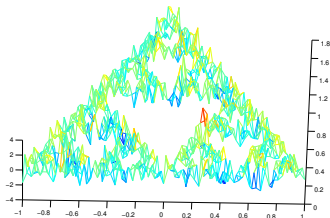
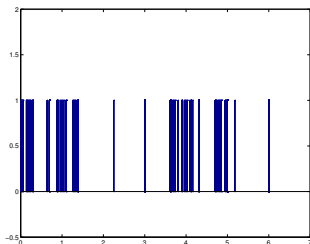
# Example

Consider the function  $g_0 : V \rightarrow \mathbb{R}$  by setting  $\hat{g}_0(\lambda_l) = 1$  for all  $l = 0, \dots, N-1$ . Then,

$$g_0(n) = \sum_{l=0}^{N-1} \varphi_l(n).$$

Then for any signal  $f : V \rightarrow \mathbb{R}$

$$\begin{aligned} f(n) &= \sum_{l=0}^{N-1} \hat{f}(\lambda_l) \varphi_l(n) = \sum_{l=0}^{N-1} \hat{f}(\lambda_l) \hat{g}_0(\lambda_l) \varphi_l(n) \\ &= f * g_0(n). \end{aligned}$$



# Graph Translation

- For signal  $f \in L^2(\mathbb{R})$ , the translation operator,  $T_u$ , can be thought of as a convolution with  $\delta_u$ .
- On  $\mathbb{R}$  we can calculate
$$\hat{\delta}_u(k) = \int_{\mathbb{R}} \delta_u(x) e^{-2\pi i k x} dx = e^{2\pi i k u} (= \varphi_k(u)).$$
- Then by taking the convolution on  $\mathbb{R}$  we have

$$(T_u f)(t) = (f * \delta_u)(t) = \int_{\mathbb{R}} \hat{f}(k) \hat{\delta}_u(k) \varphi_k(t) dk = \int_{\mathbb{R}} \hat{f}(k) \varphi_k^*(u) \varphi_k(t) dk$$

## Definition

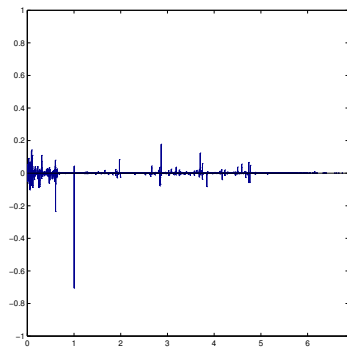
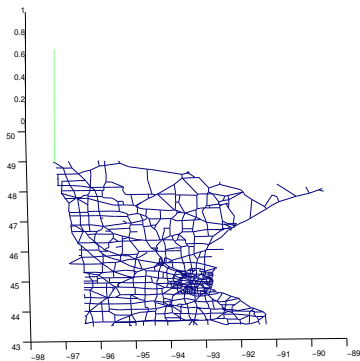
For any  $f : V \rightarrow \mathbb{R}$  the *graph translation operator*,  $T_i$ , is defined to be

$$(T_i f)(n) = \sqrt{N} (f * \delta_i)(n) = \sqrt{N} \sum_{l=0}^{N-1} \hat{f}(\lambda_l) \varphi_l^*(i) \varphi_l(n).$$

# Example - Movie

$G = \text{Minnesota}$

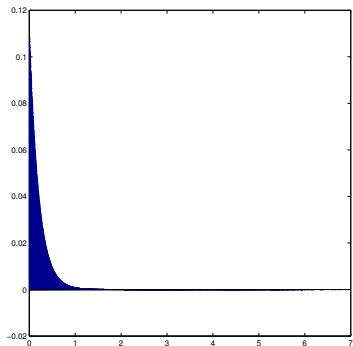
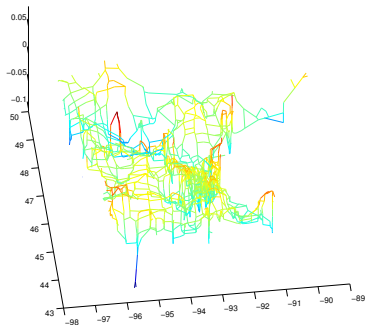
$f = \mathbb{1}_1$



# Example - Movie

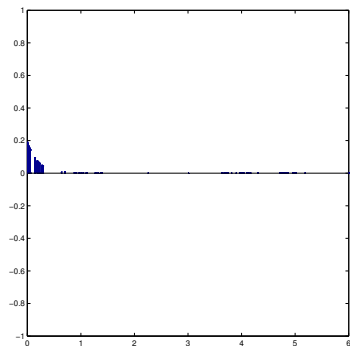
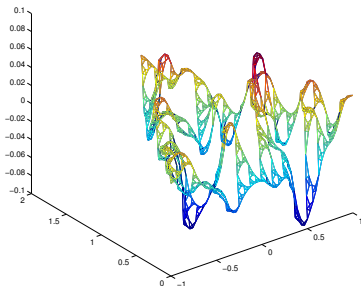
$G = \text{Minnesota}$

$$\hat{f}(\lambda_l) = e^{-5\lambda_l}$$



# Example - Movie

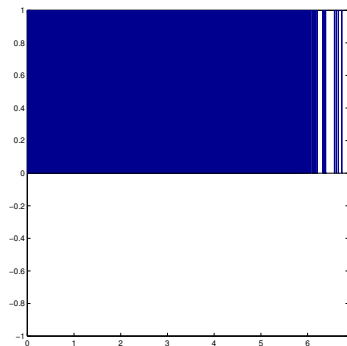
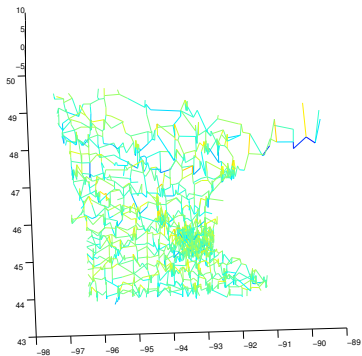
$$G = SG_6$$
$$\hat{f}(\lambda_l) = e^{-5\lambda_l}$$



# Example - Movie

$G = \text{Minnesota}$

$\hat{f} \equiv 1$



# Properties of Translation operator

The generalized graph translation possesses many of the nice properties of our usual notion of translation in Euclidean space.

## Proposition

For any  $f, g : V \rightarrow \mathbb{R}$  and  $i, j \in \{1, 2, \dots, N\}$  then

- 1  $T_i(f * g) = (T_i f) * g = f * (T_i g).$
- 2  $T_i T_j f = T_j T_i f.$

# Properties of Translation operator

## Corollary

*Given a graph,  $G$ , with real valued eigenvectors. For any  $i, n \in \{1, \dots, N\}$  and for any function  $f : V \rightarrow \mathbb{R}$  we have*

$$T_i f(n) = T_n f(i).$$

## Corollary

*Given a graph,  $G$ , with real valued eigenvectors. Let  $\alpha$  be a multiindex, i.e.  $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_K)$  where  $\alpha_j \in \{1, \dots, N\}$  for  $1 \leq j \leq K$  and let  $\alpha_0 \in \{1, \dots, N\}$ . We let  $T_\alpha$  denote the composition  $T_{\alpha_1} \circ T_{\alpha_2} \circ \dots \circ T_{\alpha_K}$ . Then for any  $f : V \rightarrow \mathbb{R}$ , we have*

$$T_\alpha f(\alpha_0) = T_\beta f(\beta_0),$$

*where  $\beta = (\beta_1, \dots, \beta_K)$  and  $(\beta_0, \beta_1, \beta_2, \dots, \beta_K)$  is any permutation of  $(\alpha_0, \alpha_1, \dots, \alpha_K)$ .*



# Not-so-nice Properties of Translation operator

- In general, the set of translation operators  $\{T_i\}_{i=1}^N$  do not form a group like in the classical Euclidean setting.
- $T_i T_j \neq T_{i+j}$ .
- If  $\Phi$  is the DFT matrix, then  $T_i T_j = T_{i+j \pmod{N}}$ .
- In general, Can we even hope for  $T_i T_j = T_{i \bullet j}$  for some semigroup operation,  $\bullet : \{1, \dots, N\} \times \{1, \dots, N\} \rightarrow \{1, \dots, N\}$ ?

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# When is graph translation a semigroup operation?

## Theorem (B. & O.)

*Given a graph,  $G$ , with eigenvector matrix  $\Phi = [\varphi_0 | \cdots | \varphi_{N-1}]$ . Graph translation on  $G$  is a semigroup, i.e.  $T_i T_j = T_{i \bullet j}$  for some semigroup operator  $\bullet : \{1, \dots, N\} \times \{1, \dots, N\} \rightarrow \{1, \dots, N\}$ , only if  $\Phi = (1/\sqrt{N})H$ , where  $H$  is a Hadamard matrix.*

- $H$  is a Hadamard matrix only if  $N = 1, 2$ , or  $4k$ . Sufficiency is open conjecture.

## Theorem (Barik, Fallat, Kirkland)

*If  $G$  has a normalized Hadamard eigenvector matrix,  $\Phi = (1/\sqrt{N})H$ , then  $G$  must be  $k$ -regular and all eigenvalues must be even integers.*

# Not-so-nice Properties of Translation operator

- The translation operator is not isometric.
- $\|T_i f\|_{\ell^2} \neq \|f\|$
- We do have the following estimates on the operator  $T_i$ :

$$|\hat{f}(0)| \leq \|T_i f\|_{\ell^2} \leq \sqrt{N} \max_{l \in \{0, 1, \dots, N-1\}} \|\varphi_l\|_{\infty} \|f\|_{\ell^2}$$

- Additionally  $T_i$  is need not be injective, and therefore not invertible.

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# Windowed Graph Fourier Transform

- Given a window function  $g : V \rightarrow \mathbb{R}$ , we define a *windowed graph Fourier atom* by

$$g_{i,k}(n) := (M_k T_i g)(n) = N_{\varphi_k}(n) \sum_{l=0}^{N-1} \hat{g}(\lambda_l) \varphi_l^*(i) \varphi_l(n).$$

- The *windowed graph Fourier transform* of function  $f : V \rightarrow \mathbb{R}$  is defined by

$$Sf(i, k) := \langle f, g_{i,k} \rangle.$$

# Windowed Graph Fourier Frames

## Theorem

If  $\hat{g}(0) \neq 0$ , then  $\{g_{i,k}\}_{i=1,2,\dots,N;k=0,1,\dots,N-1}$  is a frame. That is for all  $f : V \rightarrow \mathbb{R}$ ,

$$A \|f\|_{\ell^2}^2 \leq \sum_{i=1}^N \sum_{k=0}^{N-1} |\langle f, g_{i,k} \rangle|^2 \leq B \|f\|_{\ell^2}^2$$

where

$$A := \min_{n=1,2,\dots,N} \{N \|T_n g\|_{\ell^2}^2\}, \quad B := \max_{n=1,2,\dots,N} \{N \|T_n g\|_{\ell^2}^2\}$$

And we have the estimate:

$$0 < N |\hat{g}(0)|^2 \leq A \leq B \leq N^2 \max_{l=0,1,\dots,N-2} \|\varphi_l\|_{\infty}^2 \|g\|_{\ell^2}^2.$$

## Theorem

*Provided the window,  $g$ , has non-zero mean, i.e.  $\hat{g}(0) \neq 0$ , then for any  $f : V \rightarrow \mathbb{R}$ ,*

$$f(n) = \frac{1}{N \|T_n g\|_{\ell^2}^2} \sum_{i=1}^N \sum_{k=0}^{N-1} S f(i, k) g_{i, k}(n).$$

Proof requires basic algebraic manipulations and results given on the graph translation operators.






## Other ways to represent/approximate functions

- Polynomials on graphs
  - Polynomial is defined to be a function,  $f$ , for which  $\Delta^n f = 0$  for finite  $n$ .
  - Trivial for finite graphs. Not trivial for some infinite graphs.
- Sampling
  - Also trivial for finite graphs
- Band limiting functions

What is the boundary of a graph?

- If a graph boundary,  $\partial V \subseteq V$ , is defined, this allows us to compute Dirichlet eigenvalues.
  - The Laplacian as we've defined it here corresponds to functions on graphs with Neumann boundary conditions.
- One good definition of boundary vertices are those vertices that user has special control over
  - Connections with Schrödinger Eigenmaps
- Other ways to “extract” a boundary
  - Largest radius via shortest path metric or effective resistance metric.
  - Some techniques work well on certain graphs, poorly on others.

Thank you!

-  Fan RK Chung, *Spectral Graph Theory*, vol. 92, American Mathematical Soc., 1997.
-  Pierre Vandergheynst David I Shuman, Benjamin Ricaud, *Vertex-frequency analysis on graphs*, preprint (2013).
-  David K Hammond, Pierre Vandergheynst, and Rémi Gribonval, *Wavelets on graphs via spectral graph theory*, *Applied and Computational Harmonic Analysis* **30** (2011), no. 2, 129–150.