

# Spectral Graph Theory and Discrete Poisson Equation

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Presentation for the exam of *Graph Theory*

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Summarize principal properties of a graph into a simple list of invariants.

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**Adjacency matrix**  $\rightsquigarrow$  **Laplacian matrix**

# Graph Laplacian

Let  $G = (V, E)$  be an **undirected** graph;  $d_x := \sum_{y \in V} w_{x,y}$  degree of  $x \in V$ .

## Graph Laplacian

We define **graph Laplacian** the matrix

$$\Delta(x, y) := \begin{cases} 1 - w_{x,x}/d_x, & \text{if } x = y \text{ and } d_x \neq 0; \\ -w_{x,y}/d_x, & \text{if } x \sim y; \\ 0, & \text{otherwise.} \end{cases}$$

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→ **Idea:** summarize graph information in Laplacian eigenvalues.

→ **Problem:**  $\Delta$  is in general non-symmetric. We can consider the **normalized Laplacian**

$$\mathcal{L} := D^{1/2} \Delta D^{-1/2}$$

where  $D$  is the diagonal matrix with  $D(x, x) = d_x$ .

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## Graph Laplacian [Fan Chung, *Spectral Graph Theory*]

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→ **Idea:** summarize graph information in Laplacian eigenvalues.

**Note:** A different definition is the **combinatorial Laplacian**  $L = D - A$  with  $A$  adjacency matrix and  $\mathcal{L} = D^{-1/2} L D^{-1/2}$ .

# Motivating Example

## Matrix-tree Theorem

The number of spanning trees in a graph  $G$  is

$$\frac{\prod_i \lambda_i \prod_{x \in S} d_x}{\sum_{x \in S} d_x}$$

where  $S$  is any maximum proper subset of the vertex set and  $\lambda_i$  are the eigenvalues of  $L$  restricted to  $S$ .

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## Spectral Convergence of Markov Chains

Let  $p_t$  be the distribution after  $t$  steps of a lazy random walk on a connected graph  $G$  and  $\pi(x) = \frac{d_x}{\sum_{y \in V} d_y}$  the stationary distribution. Then,

$$\|p_t - \pi\|_2 \leq \max_{i \geq 1} \left\{ \left| 1 - \frac{\lambda_i}{2} \right| \right\}^t \sqrt{\frac{\max_x d_x}{\min_y d_y}}$$

$$\Delta(x, y) := \begin{cases} 1 - w_{x,x}/d_x, & \text{if } x = y \text{ and } d_x \neq 0; \\ -w_{x,y}/d_x, & \text{if } x \sim y; \\ 0, & \text{otherwise.} \end{cases}$$

## Why Laplacian?

Let  $f : V \rightarrow \mathbb{R}$ . We can interpret  $f$  as a vector  $(f(x))_{x \in V}$  and write  $\Delta \cdot f$ , thus

$$\Delta f(x) = \sum_{y \in V} (f(x) - f(y)) \frac{w_{x,y}}{d_x}, \quad \forall x \in V$$

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## Intuition

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3-vertices path with weight 1 for each edge:

$$f : V \rightarrow \mathbb{R} \rightsquigarrow \Delta f(x) = \frac{2f(x) - f(x-1) - f(x+1)}{2}$$

$$f : \Omega \subseteq \mathbb{R} \rightarrow \mathbb{R} \rightsquigarrow \Delta f(x) = f''(x)$$

## Smallest Eigenvalue

$$\Delta f(x) = \sum_{y \in V} (f(x) - f(y)) \frac{w_{x,y}}{d_x}, \quad \forall x \in V$$

$\lambda_0$

$\lambda_0 \leq \lambda_1 \leq \dots \leq \lambda_{n-1}$  eigenvalues of  $\Delta$ , it holds

- $\lambda_0 = 0$  by taking  $f \equiv 1$  on a connected component and 0 everywhere else.
- Its multiplicity represents the connected components of  $G$ .

## Second Smallest Eigenvalue

### Variational Characterization of $\lambda_1$

$0 = \lambda_0 \leq \lambda_1 \leq \dots \leq \lambda_{n-1}$  eigenvalues of  $\mathcal{L}$ , it holds

$$\lambda_1 = \inf_{f: \sum_x f(x) d_x = 0} \frac{\overbrace{\sum_{x \sim y} (f(x) - f(y))^2 w_{xy}}^{\text{Dirichlet energy}}}{\sum_x f^2(x) d_x}$$

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→ Measures “connectivity” of the graph. **Formal intuition:** *Cheeger Inequality*

$$2h(G) \leq \lambda_1 \leq \frac{h^2(G)}{2 \max_x d_x}$$

where  $h(G) = \min \left\{ \frac{|\delta A|}{|A|} : A \subseteq V, 0 < |A| \leq \frac{1}{2}|V| \right\}$

and  $\delta A := \{(x, y) \in E : x \in A, y \in V \setminus A\}$

# Greatest Eigenvalue

$$\Delta f(x) = \sum_{y \in V} (f(x) - f(y)) \frac{w_{x,y}}{d_x}, \quad \forall x \in V$$

$\lambda_{n-1}$

$0 = \lambda_0 \leq \lambda_1 \leq \dots \leq \lambda_{n-1}$  eigenvalues of  $\Delta$ , it holds

- $\lambda_{n-1} \leq 2$ ;
- $\lambda_{n-1} = 2 \iff$  the graph is bipartite.

$\rightarrow$  By taking  $f \equiv 1$  on a set of the partition and  $f \equiv -1$  to the other set.

## Example: Path Graph $P_3$

**Setting:** Path graph  $P_3$

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**Laplacian**

$$\Delta = \begin{pmatrix} 1 & -1 & 0 \\ -1/2 & 1 & -1/2 \\ 0 & -1 & 1 \end{pmatrix} \rightsquigarrow \mathcal{L} = D^{1/2} \Delta D^{-1/2} = \begin{pmatrix} 1 & -1/\sqrt{2} & 0 \\ -1/\sqrt{2} & 1 & -1/\sqrt{2} \\ 0 & -1/\sqrt{2} & 1 \end{pmatrix}$$

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**Eigenvalues:**

- $\lambda_0 = 0$  (one connected component);
- $\lambda_1 = 1$  (graph “well-connected”);
- $\lambda_2 = 2$  (graph is bipartite).

## Example: Triangle $T_3$

**Setting:** Triangle graph  $T_3$

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**Normalized Laplacian:**

$$\mathcal{L} = \begin{pmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & 1 & -\frac{1}{2} \\ -\frac{1}{2} & -\frac{1}{2} & 1 \end{pmatrix}.$$

**Eigenvalues:**

- $\lambda_0 = 0$  (one connected component);
- $\lambda_1 = 3/2$  (graph “fully connected”);
- $\lambda_2 = 3/2 < 2$  (graph not bipartite).

## Example: The 3-Star $S_3$

**Setting:** Star graph  $S_3$

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**Normalized Laplacian:**

$$\mathcal{L} = \begin{pmatrix} 1 & -\frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{3}} \\ -\frac{1}{\sqrt{3}} & 1 & 0 & 0 \\ -\frac{1}{\sqrt{3}} & 0 & 1 & 0 \\ -\frac{1}{\sqrt{3}} & 0 & 0 & 1 \end{pmatrix}.$$

**Eigenvalues:**

- $\lambda_0 = 0$  (one connected component);
- $\lambda_1 = \lambda_2 = 1$  (graph “well-connected”, symmetry);
- $\lambda_3 = 2$  (graph is bipartite).

# Discrete Poisson Equation

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# Discrete Poisson Equation

$$S \subseteq V, \partial S := \{y \notin S : w_{x,y} \neq 0 \text{ for some } x \in S\}$$

## Equation [Chung, Yau, *Discrete Green's Functions*]

For  $f : S \cup \partial S \rightarrow \mathbb{R}$ ,  $g : S \rightarrow \mathbb{R}$  and  $\sigma : \partial S \rightarrow \mathbb{R}$

$$\begin{cases} \Delta_S f(x) = g(x), & \text{for } x \in S; \\ f(x) = \sigma(x), & \text{for } x \in \partial S. \end{cases}$$

# Motivating Example

## Electric Networks

Let  $G = (V, E)$  represent an **electric network**, the discrete Poisson equation is used to describe **diffusion**.

- $g$ : external current source on the network;
- $f$ : potential at the nodes;
- $\sigma$ : fixed potential it in the boundary vertices.

$$\begin{cases} \Delta f(x) = g(x), & \text{for } x \in S; \\ f(x) = \sigma(x), & \text{for } x \in \partial S. \end{cases}$$

# Solving Discrete Poisson Equation

## Solution Strategy

As for continuous PDEs,

→ Find  $f^{(1)}$  solution of

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→ Define the solutions of the discrete Poisson equation as  $f = f^{(1)} + f^{(2)}$

# Solution of $\Delta f^{(1)} = 0$

## Solution form

$f^{(1)}$  solution of

$$\begin{cases} \Delta_S f(x) = 0, & \text{for } x \in S; \\ f(x) = \sigma(x), & \text{for } x \in \partial S. \end{cases}$$

have the form

$$f^{(1)}(z) = \sum_i \left( \frac{1}{\lambda_i} \sum_{x \in S: x \sim y \in \partial S} \sqrt{d_x} \varphi_i(x) \sigma(y) \right) d_z^{-1/2} \varphi_i, \quad \forall z \in S$$

where  $\lambda_i$  eigenvalues and  $\varphi_i$  eigenfunctions of  $\Delta_S$ .

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## Proof idea

→ We consider  $\tilde{f}^{(1)}(x) = D^{1/2} f^{(1)}(x)$  satisfying  $\mathcal{L}_S \tilde{f}^{(1)}(x) = 0$  on  $S$ .

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- We can write  $\tilde{f}^{(1)} = \sum_i \langle \varphi_i, \tilde{f}^{(1)} \rangle \varphi_i$ .
- Explicitly compute  $\langle \varphi_i, \tilde{f}^{(1)} \rangle$  using the boundary condition  $\sigma$ .

## Particular solution of $\Delta f^{(2)} = g$

### Discrete Green's Function

If  $\partial S \neq \emptyset$  and  $S$  is connected, we define the **Discrete Green's Function**  $G_S$  as

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We have

$$G_S(x, y) = \sum_i \frac{1}{\lambda_i} d_x^{1/2} \varphi_i(x) \varphi_i(y) d_y^{-1/2}, \quad \text{for } x, y \in S.$$

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## Solution form

We can take as solution of  $\Delta_S f^{(2)} = g$  with boundary condition  $f^{(2)} = 0$  on  $\partial S$  the function

$$f^{(2)} = G_S g$$

# Solution of Discrete Poisson Equation

## Solution Form

Solution of the Discrete Poisson Equation

$$\begin{cases} \Delta_S f(x) = g(x), & \text{for } x \in S; \\ f(x) = \sigma(x), & \text{for } x \in \delta S. \end{cases}$$

are of the form  $f = f^{(1)} + f^{(2)}$  with  $f^{(1)}$  and  $f^{(2)}$  computed as in the previous slides.

## Application: Hitting Probability

**Problem:** Compute probability  $f_{x,y}(z)$  that an irreducible Markov chain hits  $x$  before  $y$  starting from  $z$ .

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**Discrete Poisson Equation:**  $f_{x,y}(z)$  is the solution of

$$\begin{cases} \Delta_S f_{x,y}(z) = 0, & z \in S \\ f_{x,y}(z) = \sigma(z), & z \in \partial S \end{cases}$$

## Application: Hitting Probability

**Setting:**  $P_3$  path graph.

**Solution:** We can compute explicitly  $\Delta f_{1,3}(2) = 0$  with boundary conditions  $\sigma(1) = 1, \sigma(3) = 0$ .

$$\frac{2f_{1,3}(2) - f_{1,3}(1) - f_{1,3}(3)}{2} = 0 \implies \frac{2f_{1,3}(2) - 1 - 0}{2} = 0 \implies f_{1,3}(2) = \frac{1}{2}$$

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**Thank you for your attention!**