

# Laplacians and Eigenvalues

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## The standard Laplacian

Graph  $G$ , vertices numbered  $1, \dots, n$ . Degrees  $d_1, \dots, d_n$ .

Adjacency matrix  $A$ , degree matrix  $T = \text{diag}(d_1, \dots, d_n)$ , incidence matrix  $E$ :

$$E(u, e) = \begin{cases} +1, & \text{if } u \text{ incident to } e = \{u, v\} \text{ with orientation } e : u \rightarrow v, \\ -1, & \text{if } u \text{ incident to } e = \{u, v\} \text{ with orientation } e : v \rightarrow u, \\ 0, & \text{otherwise.} \end{cases}$$

*Standard Laplacian*  $L = EE^*$ :

$$L(u, v) = \sum_e E(u, e)E(v, e) = \begin{cases} d_u, & \text{if } u = v, \\ -1, & \text{if } u \neq v, u \sim v, \\ 0, & \text{otherwise.} \end{cases}$$

Thus also  $L = T - A$ .

## The normalised Laplacian

For  $k$ -regular  $G$ , natural to consider also normalised Laplacian

$$\mathcal{L} = \frac{1}{k}L = I - \frac{1}{k}A.$$

In general, define *normalised incidence matrix*  $S$ :

$$S(u, e) = \begin{cases} +1/\sqrt{d_u}, & \text{if } u \text{ incident to } e = \{u, v\} \text{ with orientation } e : u \rightarrow v, \\ -1/\sqrt{d_u}, & \text{if } u \text{ incident to } e = \{u, v\} \text{ with orientation } e : v \rightarrow u, \\ 0, & \text{otherwise.} \end{cases}$$

Then define *normalised Laplacian*  $\mathcal{L} = SS^*$ :

$$\mathcal{L}(u, v) = \sum_e S(u, e)S(v, e) = \begin{cases} 1, & \text{if } u = v, \\ -1/\sqrt{d_u d_v}, & \text{if } u \neq v, u \sim v, \\ 0, & \text{otherwise.} \end{cases}$$

## Relation to standard Laplacian

Denote

$$T^{1/2} = \text{diag}(\sqrt{d_1}, \dots, \sqrt{d_n}).$$

Since for all vertices  $u, v$  in  $G$ :

$$\mathcal{L}(u, v) = \frac{L(u, v)}{\sqrt{d_u d_v}},$$

one obtains representation

$$\mathcal{L} = T^{-1/2} L T^{-1/2} = I - T^{-1/2} A T^{-1/2}.$$

[Note that

$$L T^{-1/2}(u, v) = \sum_w L(u, w) T^{-1/2}(w, v) = L(u, v) \cdot \frac{1}{\sqrt{d_v}}$$

$$T^{-1/2} L(u, v) = \sum_w T^{-1/2}(u, w) L(w, v) = \frac{1}{\sqrt{d_u}} \cdot L(u, v).]$$

## The Laplacian as operator

Consider an assignment of vertex potentials  $g : V(G) \rightarrow \mathbb{R}$ . Then:

$$Lg(u) = (T - A)g(u) = d_u \cdot g(u) - \sum_{v \sim u} g(v) = \sum_{v \sim u} (g(u) - g(v)).$$

For  $k$ -regular  $G$ , the normalised Laplacian yields:

$$\mathcal{L}g(u) = (I - \frac{1}{k}A)g(u) = g(u) - \frac{1}{k} \sum_{v \sim u} g(v) = \frac{1}{k} \sum_{v \sim u} (g(u) - g(v)).$$

For general  $G$ , the normalised Laplacian yields:

$$\begin{aligned} \mathcal{L}g(u) &= (I - T^{-1/2}AT^{-1/2})g(u) \\ &= g(u) - \sum_{v \sim u} \frac{g(v)}{\sqrt{d_u d_v}} = \frac{1}{\sqrt{d_u}} \sum_{v \sim u} \left( \frac{g(u)}{\sqrt{d_u}} - \frac{g(v)}{\sqrt{d_v}} \right). \end{aligned}$$

This leads to the notion of *normalised (harmonic) potentials*:

$$f(u) = T^{-1/2}g(u) = \frac{g(u)}{\sqrt{d_u}}.$$

## Laplacian eigenvalues

Since  $\mathcal{L}$  is symmetric, all its eigenvalues are real. Consider an eigenvalue  $\lambda$  with associated eigenvector  $g$ :

$$\begin{aligned} \mathcal{L}g = \lambda g &\iff (T^{-1/2} \mathcal{L} T^{-1/2})g = \lambda g \\ &\iff L(T^{-1/2}g) = \lambda(T^{-1/2}g) \\ &\iff Lf = \lambda T f \\ &\iff (T^{-1}L)f = \lambda f. \end{aligned}$$

Thus  $g$  is eigenvector of  $\mathcal{L}$  with eigenvalue  $\lambda$

$$\iff f = T^{-1/2}g \text{ is eigenvector of } T^{-1}L \text{ with eigenvalue } \lambda.$$

I.e.  $\mathcal{L}$  has same spectrum as  $T^{-1}L$ , with “normalised” eigenvectors.

$$T^{-1}L = T^{-1}T - T^{-1}A = I - T^{-1}A,$$

$$T^{-1}L(u, v) = \begin{cases} 1, & \text{if } u = v, \\ -1/d_u, & \text{if } u \neq v, u \sim v, \\ 0, & \text{otherwise.} \end{cases}$$

## Rayleigh quotient

$$\begin{aligned}
 \frac{\langle g, \mathcal{L}g \rangle}{\langle g, g \rangle} &= \frac{\langle g, T^{-1/2} L T^{-1/2} g \rangle}{\langle g, g \rangle} \\
 &= \frac{\langle T^{1/2} f, T^{-1/2} L f \rangle}{\langle T^{1/2} f, T^{1/2} f \rangle} \\
 &= \frac{\langle f, L f \rangle}{\langle f, T f \rangle} \\
 &= \frac{\sum_u f(u) \sum_{v \sim u} (f(u) - f(v))}{\sum_u f(u) \cdot d_u f(u)} \\
 &= \frac{\sum_{u \sim v} (f(u)^2 + f(v)^2 - 2f(u)f(v))}{\sum_u f(u)^2 d_u} \\
 &= \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u f(u)^2 d_u}
 \end{aligned}$$

## Variational characterisations

Enumerate eigenvalues of  $\mathcal{L}$  as  $\lambda_0 \leq \lambda_1 \leq \dots \leq \lambda_{n-1}$ . Then:

$$\lambda_0 = \inf_g \frac{\langle g, \mathcal{L}g \rangle}{\langle g, g \rangle} = \inf_f \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u f(u)^2 d_u} = 0.$$

Clearly  $\lambda_0 = 0$  has eigenvector  $f \equiv 1$ , i.e.

$$g = T^{1/2} \mathbf{1} = (\sqrt{d_1}, \dots, \sqrt{d_n}).$$

The next eigenvalue  $\lambda_G = \lambda_1$  is given by:

$$\lambda_1 = \inf_{g \perp T^{1/2} \mathbf{1}} \frac{\langle g, \mathcal{L}g \rangle}{\langle g, g \rangle} = \inf_{f \perp T \mathbf{1}} \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u f(u)^2 d_u}.$$

Note that

$$f \perp T \mathbf{1} \iff \sum_u f(u) d_u = 0.$$



## Variational characterisations (cont'd)

The eigenvalue  $\lambda_1$  can also be characterised as follows (exercise):

$$\lambda_1 = \inf_f \sup_t \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u (f(u) - t)^2 d_u}$$

and

$$\lambda_1 = \inf_f \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u (f(u) - \bar{f})^2 d_u},$$

where

$$\bar{f} = \frac{\sum_u f(u) d_u}{\sum_u d_u}.$$

Denoting  $\sum_u d_u = \text{vol } G$ , one has yet another characterisation:

$$\lambda_1 = \text{vol } G \cdot \inf_{f \neq 0} \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_{u:v} (f(u) - f(v))^2 d_u d_v},$$

where  $\sum_{u:v}$  denotes summation over all unordered pairs of vertices  $u, v$  in  $G$  with possibly  $u = v$ .

## Variational characterisations (cont'd)

In general,

$$\begin{aligned}\lambda_k &= \inf_{f \perp TP_{k-1}} \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u f(u)^2 d_u} \\ &= \inf_{f \neq 0} \sup_{g \in P_{k-1}} \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u (f(u) - g(u))^2 d_u},\end{aligned}$$

where  $P_{k-1}$  denotes the subspace spanned by eigenvectors associated to eigenvalues  $\lambda_0 \dots \lambda_{k-1}$ .

Finally,

$$\lambda_{n-1} = \sup_f \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u f(u)^2 d_u}.$$

## Basic properties

Graph  $G$  with  $n$  vertices.

1.  $\sum_i \lambda_i \leq n$ , with equality iff  $G$  has no isolated vertices.
2.  $\lambda_1 \leq n/(n-1)$  for  $n \geq 2$ , with equality iff  $G$  is complete.  
 $\lambda_{n-1} \geq n/(n-1)$ , unless  $G$  has isolated vertices.
3.  $\lambda_1 \leq 1$ , unless  $G$  is complete.
4.  $\lambda_1 > 0$ , if  $G$  is connected.  
 More generally, if  $i$  is smallest index for which  $\lambda_i > 0$ , then  $G$  has exactly  $i$  connected components.
5.  $\lambda_i \leq 2$  for all  $i$ , with  $\lambda_{n-1} = 2$  iff  $G$  has a nontrivial bipartite component.
6. The spectrum of  $G$  is the union of the spectra of its connected components.

## Bipartite graphs

The following are equivalent:

1.  $G$  is bipartite.
2.  $G$  has  $i$  connected components, and  $\lambda_{(n-1)-j} = 2$  for  $j = 1, \dots, i$ .
3. For each  $\lambda_j$ , also  $2 - \lambda_j$  is eigenvalue of  $G$ .

## A lower bound for $\lambda_1$

*Diameter* of graph = max shortest-path distance between any two vertices.

**Theorem.** For a connected graph  $G$  with diameter  $D$ ,

$$\lambda_1 \geq \frac{1}{D \operatorname{vol} G}.$$

*Proof.*

Choose harmonic potential  $f$  associated to  $\lambda_1$ .

Choose vertex  $u_0$  with  $|f(u_0)| = \max$ .

Since  $f \perp T1$ , there is some vertex  $v_0$  s.th.  $f(u_0)f(v_0) < 0$ . Denote shortest path connecting  $u_0$  and  $v_0$  by  $P$ .

## A lower bound for $\lambda_1$ (cont'd)

Then:

$$\begin{aligned}
 \lambda_1 &= \frac{\sum_{u \sim v} (f(u) - f(v))^2}{\sum_u f(u)^2 d_u} \\
 &\geq \frac{\sum_{\{u,v\} \in P} (f(u) - f(v))^2}{f(u_0)^2 \cdot \sum_u d_u} \\
 &\geq \frac{\frac{1}{D} (f(u_0) - f(v_0))^2}{f(u_0)^2 \cdot \text{vol } G} \\
 &\geq \frac{1}{D \text{ vol } G}.
 \end{aligned}$$

The next-to-last inequality follows by Cauchy-Schwartz:

$$\sum_{\{u,v\} \in P} (f(u) - f(v))^2 \geq \frac{1}{D} \left[ \sum_{\{u,v\} \in P} (f(u) - f(v)) \right]^2 = \frac{1}{D} (f(u_0) - f(v_0))^2.$$

## Miscellaneous

**Proposition.** Let  $f$  be a harmonic potential associated to eigenvalue  $\lambda$ . Then for any vertex  $u$ ,

$$\frac{1}{d_u} \sum_{v \sim u} (f(u) - f(v)) = \lambda f(u).$$

*Proof.* Follows by comparing coefficients in  $T^{-1}Lf = \lambda f$ .

**Theorem.** For a  $k$ -regular graph with  $n$  vertices,

$$\max_{i > 0} |1 - \lambda_i| \geq \sqrt{\frac{n-k}{(n-1)k}}.$$

## Weighted graphs

Given graph  $G$  with vertex set  $V$ , weight function  $w : V \times V \rightarrow \mathbb{R}$  satisfying:

- ▶  $w(u, v) = w(v, u)$  for all  $u, v$ ,
- ▶  $w(u, v) \geq 0$  for all  $u, v$ ,
- ▶  $w(u, v) > 0$  only if  $u \sim v$  in  $G$ .

Define:

- ▶ *degree* of vertex  $u$ :  $d_u = \sum_v w(u, v)$ .
- ▶ *volume* of graph  $G$ :  $\text{vol } G = \sum_u d_u$ .



## Laplacians of weighted graphs

Standard Laplacian:

$$L(u, v) = \begin{cases} d_u - w(u, u), & \text{if } u = v, \\ -w(u, v), & \text{if } u \neq v, u \sim v, \\ 0, & \text{otherwise.} \end{cases}$$

Thus,

$$Lf(u) = \sum_{v \sim u} (f(u) - f(v))w(u, v).$$

Normalised Laplacian:  $\mathcal{L} = T^{-1/2}LT^{-1/2}$ .

Thus,

$$\mathcal{L}(u, v) = \begin{cases} 1 - \frac{w(u, u)}{d_u}, & \text{if } u = v, \\ -\frac{w(u, v)}{\sqrt{d_u d_v}}, & \text{if } u \neq v, u \sim v, \\ 0, & \text{otherwise.} \end{cases}$$

## Variational characterisations

The previous characterisations still hold, *mutatis mutandis*. E.g.

$$\begin{aligned}\lambda_G := \lambda_1 &= \inf_{g \perp T^{1/2} \mathbf{1}} \frac{\langle g, \mathcal{L}g \rangle}{\langle g, g \rangle} \\ &= \inf_{\sum f(u) d_u = 0} \frac{\sum_{u \sim v} (f(u) - f(v))^2 w(u, v)}{\sum_u f(u)^2 d_u}.\end{aligned}$$

## Contractions

A *contraction* of a graph is formed by identifying two distinct vertices  $u$ ,  $v$  into a single vertex  $u^*$ . The weights of edges incident to  $u^*$  are determined as follows:

$$w(x, u^*) = w(x, u) + w(x, v)$$

$$w(u^*, u^*) = w(u, u) + w(v, v) + 2w(u, v).$$

**Theorem.** If graph  $H$  is formed by contractions from graph  $G$ , then

$$\lambda_G \leq \lambda_H.$$