# 1 Spectral Graph Theory

We assume the graph has $n$ vertices and $m$ edges. The vertex set is $V$ and the edge set is $E$.

## 1.1 Courant-Fischer Theorem

1. **Eigenvalue version**: Let $A$ be a symmetric matrix with eigenvalues $\lambda_1 \le \cdots \le \lambda_n$, then
$$\lambda_i = \min_{\substack{\text{subspace } W \subseteq \mathbb{R}^n \\ \dim(W)=i}} \max_{\substack{x \in W \\ x \ne \mathbf{0}}} \frac{x^\top A x}{x^\top x} = \max_{\substack{\text{subspace } W \subseteq \mathbb{R}^n \\ \dim(W)=n+1-i}} \min_{\substack{x \in W \\ x \ne \mathbf{0}}} \frac{x^\top A x}{x^\top x}.$$
2. **Eigenbasis version**: Let $A$ be a symmetric matrix with eigenvalues $\lambda_1 \le \cdots \le \lambda_n$ and corresponding orthonormal eigenvectors $x_1, \ldots, x_n$, then
$$\lambda_i = \min_{\substack{x \perp x_1, \ldots x_{i-1} \\ x \ne \mathbf{0}}} \frac{x^\top A x}{x^\top x} = \max_{\substack{x \perp x_{i+1}, \ldots x_n \\ x \ne \mathbf{0}}} \frac{x^\top A x}{x^\top x}.$$

Note that we also have $\lambda_i = \frac{x_i^\top A x_i}{x_i^\top x_i}$.

Applying Courant-Fischer theorem, we have $\lambda_2 x^\top x \le x^\top L x \le \lambda_n x^\top x$ for all $x \perp \mathbf{1}$, as $\mathbf{1}$ is the eigenvector of $L$ corresponding to eigenvalue 0. For connected graphs, $\lambda_2 > 0$.

## 1.2 PSD Order (Loewner Order)

Defined only for symmetric matrices: $A \preceq B$ iff for all $x \in \mathbb{R}^n$, we have $x^\top A x \le x^\top B x$. We also define $G \preceq H$ for two graphs $G$ and $H$ iff $L_G \preceq L_H$. We always have $G \succeq H$ if $H$ is a subgraph of $G$.

Properties:
1. If $A \preceq B$ and $B \preceq C$, then $A \preceq C$.
2. If $A \preceq B$, then $A + C \preceq B + C$ for any symmetric $C$.
3. If $A \preceq B$ and $C \preceq D$, then $A + C \preceq B + D$.
4. If $A \succ 0$ and $\alpha \ge 1$, then $\frac{1}{\alpha} A \preceq A \preceq \alpha A$.
5. If $A \preceq B$, then $\lambda_i(A) \le \lambda_i(B)$ for all $i$. Proof by Courant-Fischer theorem. The converse is not true.
6. For any matrix $C$, if $A \preceq B$, then $C^\top A C \preceq C^\top B C$.
7. If $0 \preceq A \preceq B$, then $B^{-1} \preceq A^{-1}$.

## 1.3 Bounding the $\lambda_2$ and $\lambda_n$

### 1.3.1 Test Vector Method

Since $\lambda_2 \le \frac{y^\top L y}{y^\top y}$ for any $y \perp \mathbf{1}$, we can upper bound the $\lambda_2$ by any **test vector** $y$. Similarly, we can lower bound the $\lambda_n$ by test vectors by $\lambda_n \ge \frac{y^\top L y}{y^\top y}$.

1. For a complete graph $K_n$, $L = n\boldsymbol{I} - \mathbf{1}\mathbf{1}^\top$ and for any $x \perp \mathbf{1}$ we have $x^\top L x = n x^\top x$. Therefore, $\lambda_2(K_n) = \cdots = \lambda_n(K_n) = n$ and any $x \perp \mathbf{1}$ is an eigenvector.
2. For a path graph $P_n$, let $x(i) = n + 1 - 2i$ be the test vector which satisfies $x \perp \mathbf{1}$, we get $\lambda_2(P_n) \le \frac{12}{n^2}$. Let $x(1) = -1$, $x(n) = 1$ and $x(i) = 0$ for other $i$ to be the test vector, we get $\lambda_n(P_n) \ge 1$.
3. For a complete binary tree $T_n$ (depth equals zero for a single root), let $x(i) = 0$ for all non-leaf nodes, $x(i) = -1$ for even-numbered leaf nodes and $x(i) = 1$ for odd-numbered leaf nodes be the test vector, we get $\lambda_n(T_n) \ge 1$. Let $x(1) = 0$, $x(i) = 1$ for the left subtree of the root and $x(i) = -1$ for the right subtree of the root be the test vector, we get $\lambda_2(T_n) \le \frac{2}{n-1}$.

### 1.3.2 Consequences of PSD Order

Since $x^\top(D - A)x = \sum_{(u,v)} w(u,v)(x(u) - x(v))^2 \ge 0$ and $x^\top(D + A)x = \sum_{(u,v)} w(u,v)(x(u) + x(v))^2 \ge 0$, we have $D \succeq A$ and $D \succeq -A$. In addition, we have $D \preceq (\max D_{i,i})\boldsymbol{I}$. Therefore, we have $L = D - A \preceq 2D \preceq (2\max D_{i,i})\boldsymbol{I}$, which implies $\lambda_n \le 2\max D_{i,i}$ for any graph. For unit-weight graphs, this means $\lambda_n \le 2\max \operatorname{degree}(v)$. The bound is tight for a single-edge graph.

To get lower bounds of $\lambda_2(H)$, we first establish $f(n)H \succeq G$ for some $G$ with known lower bounds on $\lambda_2(G)$. Usually $G = K_n$ because $\lambda_2(K_n) = n$. Then it follows that $\lambda_2(H) \ge \lambda_2(G)/f(n)$.

1. **Path Graph** $P_n$: Let $G_{i,j}$ denote a unit-weight graph consisting of one edge $(i,j)$ and $P_n$ be the path graph connecting 1 and $n$. Then $(n-1)P_n \succeq G_{1,n}$. Proof follows from applying Cauchy-Schwartz for $\delta_i := x(i+1) - x(i)$. For weighted paths, we have $G_{1,n} \preceq \left(\sum_{i=1}^{n-1} \frac{1}{w_i}\right) \sum_{i=1}^{n-1} w_i G_{i,i+1}$.
   Applying path inequality, we have $K_n = \sum_{i<j} G_{i,j} \preceq \sum_{i<j}(j-i)P_{i,j} \preceq \sum_{i<j}(j-i)P_n \preceq n^3 P_n$, which implies $\lambda_2(P_n) \ge \lambda_2(K_n)/n^3 = 1/n^2$.
2. **Any unit-weight graph** $G$: Define the diameter $D$ of a graph $G$ to be the maximum length of the shortest paths between any two nodes. Let $G_{i,j}^s$ be the shortest path from $i$ to $j$. Applying path inequality, we have $K_n = \sum_{i<j} G_{i,j} \preceq \sum_{i<j} D G_{i,j}^s \preceq \sum_{i<j} DG \preceq n^2 DG$, which implies $\lambda_2(G) \ge \frac{1}{nD}$.
3. **Complete Binary Tree** $T_n$: Define $G_e$ be the single-edge graph with edge $e$, and $T_{i,j}$ be the unique path between $i$ and $j$. Applying the weighted path inequality, we have $K_n = \sum_{i<j} G_{i,j} \preceq \sum_{i<j}\left(\left(\sum_{e \in T^{i,j}} \frac{1}{w(e)}\right)\left(\sum_{e \in T^{i,j}} w(e) G_e\right)\right) \preceq \left(\max_{i<j} \sum_{e \in T^{i,j}} \frac{1}{w(e)}\right)\left(\sum_{i<j} \sum_{e \in T^{i,j}} w(e) G_e\right)$. For $e$ connecting level $i$ and $i+1$ for $i \in [d-1]$, we set $w(e) = 2^i$. Then $\max_{i<j} \sum_{e \in T^{i,j}} \frac{1}{w(e)} \le 4$. Since the number of occurrence of $e$ in $T^{i,j}$ for any $i < j$ is upper bounded by $n^2 2^{-i}$, we have $\sum_{i<j} \sum_{e \in T^{i,j}} w(e) G_e \preceq \sum_e w(e) n^2 2^{-i} G_e = \sum_e n^2 G_e = n^2 T_n$. Therefore, $K_n \preceq 4n^2 T_n$, which implies $\lambda_2(T_n) \ge \frac{1}{4n}$.

# 2 Conductance

Definitions:
1. **Conductance of a vertex subset**: Given $\emptyset \subset S \subset V$, the conductance $\phi(S) := \phi(S) = \frac{|E(S, V \setminus S)|}{\min\{\mathbf{vol}(S), \mathbf{vol}(V \setminus S)\}}$, where $\mathbf{vol}(S) := \sum_{v \in S} \operatorname{degree}(v)$. Define $\mathbf{1}_S$ to be the $n$-dimensional vector with only 1 for the vertices of $S$ and 0 for the vertices of $V \setminus S$. Assuming $\mathbf{vol}(S) \le \mathbf{vol}(V)/2$, thus $|E(V, V \setminus S)| = \sum_{(u,v) \in E}(\mathbf{1}_S(u) - \mathbf{1}_S(v))^2 = \mathbf{1}_S^\top L \mathbf{1}_S$ and $\mathbf{vol}(S) = \mathbf{1}_S^\top D \mathbf{1}_S$. Then $\phi(S) = \frac{\mathbf{1}_S^\top L \mathbf{1}_S}{\mathbf{1}_S^\top D \mathbf{1}_S}$.
2. **Conductance of a graph**: The conductance $\phi(G) := \min_{\emptyset \subset S \subset V} \phi(S) = \min_{\substack{\emptyset \subset S \subset V \\ \mathbf{vol}(S) \le \mathbf{vol}(V)/2}} \phi(S)$.
3. **$\phi$-expander**: For any $\phi \in (0,1]$, we call a graph $G$ to be a $\phi$-expander if $\phi(G) \ge \phi$.
4. **$\phi$-expander decomposition of quality** $q$: A partition $\{X_i\}$ of the vertex set $V$ is called a $\phi$-expander decomposition of quality $q$ if (1) each induced graph $G[X_i]$ is a $\phi$-expander, and (2.i) #edges not contained in any $G[X_i]$ is at most $q \cdot \phi \cdot m$. The second condition is equivalent to (2.ii) The partition removes at most $q \cdot \phi \cdot m$ edges.
5. **Normalized Laplacian**: We define the *normalized Laplacian* to be $N := D^{-1/2} L D^{-1/2}$. $N$ is still PSD, with first eigenvalue equals 0 associated with eigenvector $D^{1/2}\mathbf{1}$. By Courant-Fischer theorem, $\lambda_2(N) = \min_{x \perp D^{1/2}\mathbf{1}} \frac{x^\top N x}{x^\top x} = \min_{z \perp d} \frac{z^\top L z}{z^\top D z}$.

## 2.1 Cheeger's Inequality

Notice that the $\lambda_2(N)$ has similar forms to $\phi(G)$. Cheeger's inequality aims to bound $\phi(G)$ by $\lambda_2(N)$.

**Cheeger's Inequality**: $\frac{\lambda_2(N)}{2} \le \phi(G) \le \sqrt{2\lambda_2(N)}$.

The lower bound is proved by restricting the minimum in $\lambda_2(N)$ to be $z_S = \mathbf{1}_S - \alpha\mathbf{1}$ for some $\alpha$ such that $z_S \perp d$. The upper bound is proved by constructing $S$ for any $z \perp d$ such that $\frac{\mathbf{1}_S^\top L \mathbf{1}_S}{\mathbf{1}_S^\top D \mathbf{1}_S} \le \sqrt{2\frac{z^\top L z}{z^\top D z}}$.

# 3 Random Walks on a Graph

A **random walk on a graph** $G$ is a Markov Chain with transition probability $\mathbb{P}(v_{t+1} = v \mid v_t = u) = w(u,v)/d(u)$ iff $(u,v) \in E$ and 0 otherwise. The transition matrix is thus $W = AD^{-1} = I - D^{1/2} N D^{-1/2}$ and $p_t = W^t p_0$. Define $\boldsymbol{\pi} = \frac{d}{\mathbf{1}^\top d}$, thus $\boldsymbol{\pi} = W\boldsymbol{\pi}$ for any $G$, so every $G$ has a stationary distribution.

## 3.1 Lazy Random Walks

A **lazy random walk on a graph** $G$ is a random walk, but has half probability to not move for every step. Assuming that $G$ is connected, the lazy random walk guarantees ergodicity of the Markov Chain, and thus convergence to the stationary distribution. The transition matrix is $\tilde{W} = \frac{1}{2}(I + W) = I - \frac{1}{2} D^{1/2} N D^{-1/2}$.

**Relation between lazy random walk and normalized Laplacian**: For the $i$-th eigenvalue $\nu_i$ of $N$ associated with eigenvector $\psi_i$, the $\tilde{W}$ has an eigenvalue $1 - \frac{1}{2}\nu_i$ associated with eigenvector $D^{1/2}\psi_i$. Since $0 \preceq L \preceq 2D$, we have $0 \preceq N \preceq 2\boldsymbol{I}$ and thus $0 \le \lambda_i(N) \le 2$. Therefore, we conclude that all eigenvalues of $\tilde{W} \in [0,1]$.

**Dynamics of lazy random walk**: Expanding the starting distribution $p_0$ by the eigenvectors of $\tilde{W}$, we have for some $\{\alpha_i\}$ that $p_0 = \sum_{i=1}^n \alpha_i D^{1/2}\psi_i$. Therefore, we have $p_t = \tilde{W}^t p_0 = \sum_{i=1}^n \alpha_i (1 - \frac{1}{2}\nu_i)^t D^{1/2}\psi_i \to \alpha_1 D^{1/2}\psi_1$ as $\nu_1 = 0$ and

$\nu_i > 0$ for $i \neq 1$. Since $\psi_1 \propto D^{1/2}\mathbf{1}$, we have $\psi_1 = \frac{d^{1/2}}{(\mathbf{1}^\top d)^{1/2}}$, thus $\alpha_1 = \psi_1^\top D^{-1/2} p_0 = \frac{\mathbf{1}^\top p_0}{(\mathbf{1}^\top d)^{1/2}} = \frac{1}{(\mathbf{1}^\top d)^{1/2}}$ and $\alpha_1 D^{1/2}\psi_1 = \pi$, which implies $p_t \to \pi$, the stationary distribution.

**Rate of Convergence**: For any unit-weight connected graph $G$ and any starting distribution $p_0$, we have $\|p_t - \pi\|_\infty \le e^{-\nu_2 t/2}\sqrt{n}$. Therefore, a larger $\nu_2$ and smaller vertex set means faster convergence, and the convergence rate is exponential.

### 3.2 Hitting Time

**The expected hitting time** from $a$ to $s$ is defined by $\mathbb{E}H_{a,s}$, where $H_{a,s} = \mathbf{argmin}_t\{v_t = s \mid v_0 = a\}$. We want $\mathbb{E}H_{a,s}$ for all vertices $a$ and denote the vector as $h$, *e.g.*, $h(s) = 0$.

By one-step analysis, we have $h(a) = 1 + \sum_{(a,b)\in E} \frac{w(a,b)}{d(a)} h(b) = 1 + \mathbf{1}_a^\top W^\top h$, and thus $1 = \mathbf{1}_a^\top (\boldsymbol{I} - W^\top)h$. Combining the equation for all vertices except $s$, we have $\mathbf{1} - \alpha \mathbf{1}_s = (\boldsymbol{I} - W^\top)h$, where $\alpha$ represents the extra freedom from the $n-1$ equations. Multiplying both side by $D$, we get $d - \alpha d(s)\mathbf{1}_s = (D - A)h = Lh$, which only have solution when $d - \alpha d(s)\mathbf{1}_s \perp \mathbf{1}$. Therefore, $\alpha = \|d\|_1 / d(s)$.

To summarize, by solving $Lh = d - \|d\|_1 \mathbf{1}$, we can get the expected hitting time from all vertices to $s$. Note that the solution has one extra freedom because $\dim(\ker(L)) = 1$, and the correct expected hitting time is $h - h(s)\mathbf{1}$ to enforce the constraint that $h(s) = 1$. The equation can be solved in $\tilde{O}(m)$.

## 4 Pseudo-Inverse and Effective Resistance

Given a Laplacian $L$, its (Moore-Penrose) pseudo inverse is defined to be either of the two equivalents:

1. A matrix $L^+$ that is (1) symmetric, (2) $L^+ v = 0$ for $v \in \ker(L)$, and (3) $L^+ L v = L L^+ v = v$ for $v \in \ker(L)$.
2. Let $\lambda_i, v_i$ be the $i$-th eigenvalue and eigenvector. Then $L^+ = \sum_{\lambda_i \neq 0} \lambda_i^{-1} v_i v_i^\top$.

Property:

- Assume $M = XYX^\top$, where $X$ is real and invertible, and $Y$ is real and symmetric. Let $\Pi_M$ be the orthogonal projection to the image of $M$. Then $M^+ = \Pi_M (X^\top)^{-1} Y^+ X^{-1} \Pi_M$.
- For symmetric $L$, $\Pi_L := \sum_{\lambda_i \neq 0} v_i v_i^\top = L^{+/2} L L^{+/2} = L^+ L = L L^+$ is the orthogonal projection to the image of $L$, *i.e.*, $\Pi_L v = 0$ for any $v \in \ker(L)$ and $\Pi_v = v$ for any $v \in \mathbf{im}(L)$. For connected $G$, $\Pi_L = \boldsymbol{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^\top$.

The effective resistance between vertex $a$ and $b$ is defined to be the cost (energy lost) to routing one unit (of positive electric charge) from $a$ to $b$: $R_{\text{eff}}(a,b) = \min_{Bf = \mathbf{1}_b - \mathbf{1}_a} f^\top R f = \tilde{f}^\top R \tilde{f}$, where $\tilde{f}$ is the electric flow. Let $\tilde{x}$ be the electric voltages, we also have $L\tilde{x} = \mathbf{1}_b - \mathbf{1}_a$, and thus $R_{\text{eff}}(a,b) = \tilde{x}^\top L \tilde{x} = (\mathbf{1}_b - \mathbf{1}_a)^\top L^+ (\mathbf{1}_b - \mathbf{1}_a) = \|L^{+/2}(\mathbf{1}_b - \mathbf{1}_a)\|_2^2$.

Effective Resistance is a distance defined on the vertex pairs, i.e. $R_{\text{eff}}(a,c) \le R_{\text{eff}}(a,b) + R_{\text{eff}}(b,c)$.

## 5 Gaussian Elimination for Laplacian

### 5.1 Optimization View

Solving $Lx = d$ is equivalent to solving $\mathbf{argmin}_x -d^\top x + \frac{1}{2}x^\top L x$. By iteratively optimize over $x_i$, we get a series of similar optimizations. The final optimization is straightforward, then we can back substitute to get $x$.

### 5.2 Additive View

Given an invertible square lower/upper triangular matrix $M$, we can solve $Mx = d$ by back substitution in $O(\mathbf{nnz}(M))$, where $\mathbf{nnz}(M)$ means the number of non-zeros in $M$. Therefore, if we know the **Cholesky decomposition** $L = MM^\top$ (requires $O(n^3)$), then we can solve $Lx = d = M(M^\top x)$ by (1) solving $My = d$ then (2) solving $M^\top x = y$ in $O(\mathbf{nnz}(M))$.

However, the Laplacian is non-invertible, leading to one diagonal of $M$ equals 0. Therefore, we need to play a trick. Define $\hat{M}$ equals $M$ but has value 1 for the zero diagonal, and $\hat{D}$ be a diagonal matrix that has value 0 at the zero diagonal of $M$ and 1 otherwise. Then $L = \hat{M}\hat{D}\hat{M}^\top$, and each $\hat{M}$ is now invertible. Since $\hat{D}^+ = \hat{D}$, we can find a special solution of $Lx = d$ by (1) solving $\hat{M}z = d$, (2) computing $y = \hat{D}z$, and (3) solving $\hat{M}^\top x = y$. The solution space is obtained by adding a subspace spanned by $\mathbf{1}$.

## 6 Approximating a Dense Graph in the Spectral Domain

### 6.1 Concentration of Random Matrices

1. **Chernoff Bound for Bounded independent variables**: Suppose $\{X_i \in \mathbb{R}\}$ are independent random variables and $0 \le X_i \le R$. Let $X = \sum_i X_i$ and $\mu = \mathbb{E}X$. Then for any $0 < \epsilon \le 1$, we have $\mathbb{P}(X \ge (1+\epsilon)\mu) \le \exp(-\frac{\epsilon^2 \mu}{4R})$ and $\mathbb{P}(X \le (1-\epsilon)\mu) \le \exp(-\frac{\epsilon^2 \mu}{4R})$.
2. **Bernstein Bound for independent, zero-mean and bounded variables**: Suppose $\{X_i \in \mathbb{R}\}$ are independent, zero-mean random variables and $|X_i| \le R$. Let $X = \sum_i X_i$, and $\sigma^2 = \mathbf{Var}(X)$. Then for any $t > 0$, we have $\mathbb{P}(|X| \ge t) \le 2\exp(\frac{-t^2}{2Rt + 4\sigma^2})$.
The proof is similar to Chernoff bound. (1) $\mathbb{P}(X \ge t) = \mathbb{P}(\exp(\theta X) \ge \exp(\theta t)) \le \exp(-\theta t)\mathbb{E}(\exp(\theta X))$, (2) upper bound $\mathbb{E}(\exp(\theta X)) \le \exp(\theta^2 \sigma^2)$ given $\theta \in (0, \frac{1}{R}]$, which allows $\exp(\theta X_i) \le 1 + \theta X_i + (\theta X_i)^2$, and (3) take the minimum among $\theta \in (0, \frac{1}{R}]$.
3. **Bernstein Bound for independent, zero-mean and bounded symmetric matrices**: Suppose $\{X_i \in \mathbb{R}^{n\times n}\}$ are independent, zero-mean, symmetric random matrices and $\|X_i\| \le R$, where $\|\cdot\|$ is the spectral norm (the largest singular value). Let $X = \sum_i X_i$, and $\sigma^2 = \|\sum_{i=1}^n \mathbb{E}X_i^2\|$. Then $\mathbb{P}(\|X\| \ge t) \le 2n\exp(\frac{-t^2}{2Rt + 4\sigma^2})$.

### 6.2 Matrix Functions

Given a real-valued function $f : \mathbb{R} \to \mathbb{R}$ and a symmetric matrix $A$ with eigen-decomposition $A = V\Lambda V^\top$, we define $f(A) = Vf(\Lambda)V^\top$. This is compatible to the Taylor expansion $f(x) = \sum_i \alpha_i x^i$, as $f(A) = \sum_i \alpha A^i = V(\sum_i \alpha_i f(\Lambda))V^\top = Vf(\Lambda)V^\top$.

**Monotonicity**: Given $f : \mathcal{D} \to \mathcal{C}$ and partial orders $\le_{\mathcal{C}}$ and $\le_{\mathcal{D}}$, we call $f$ is monotonically increasing w.r.t. these orders iff for all $d_1 \le_{\mathcal{D}} d_2 \in \mathcal{D}$ we have $f(d_1) \le f(d_2)$. For matrix functions, we use the PSD order as the ordering.

Property:

- If the scalar function $f$ is monotonically increasing, then the matrix function $X \to \mathbf{Tr}(f(X))$ is monotonically increasing.
- $\log(\cdot)$ is monotonically increasing.
- The matrix function $(\cdot)^2$ and $\exp(\cdot)$ is **not** monotone.
- $\exp(A) \le \boldsymbol{I} + A + A^2$ for $\|A\| \le 1$.
- $\log(\boldsymbol{I} + A) \le A$ for $A > -\boldsymbol{I}$.

### 6.3 Approximating a Dense Graph by Sparse Graphs

Given PD matrices $A, B$ and $\epsilon > 0$, we say $A \approx_\epsilon B$ iff $\frac{1}{1+\epsilon}A \le B \le (1+\epsilon)A$. If $L_G \approx_\epsilon L_{\tilde{G}}$ and $|\tilde{E}| \ll |E|$, we call $\tilde{G}$ a spectral sparsifier of $G$.

Properties:

- Define $c_G(T) := \sum_{e \in E \cap (T \times V \setminus T)} w(e)$ to be the value of the cut $(T, V \setminus T)$. If $L_G \approx_\epsilon L_{\tilde{G}}$, then for all $T \subset V$, we have $\frac{1}{1+\epsilon}c_G(T) \le c_{\tilde{G}}(T) \le (1+\epsilon)c_G(T)$. The proof is by noticing $c_G(T) = 1_T^\top L_G 1_T$.
- $L \approx_\epsilon \tilde{L} \Leftrightarrow \Pi_L \approx_\epsilon L^{+/2}\tilde{L}L^{+/2}$, as $A \le B$ implies $C^\top A C \le C^\top B C$ for any $C \in \mathbb{R}^{n\times n}$.
- For $\epsilon \le 1$, if $\|\Pi_L - L^{+/2}\tilde{L}L^{+/2}\| \le \epsilon/2$, then $\Pi_L \approx_\epsilon L^{+/2}\tilde{L}L^{+/2}$.

Theorem: Consider a connected graph $G = (V, E, w)$, with $n = |V|$. For any $0 < \epsilon < 1$ and $0 < \delta < 1$, there exist sampling probabilities $p_e$ for each edge $e \in E$ s.t. if we include each edge $e$ in $\tilde{E}$ independently with probabilty $p_e$ and set its weight $\tilde{w}(e) = \frac{1}{p_e}w(e)$, then with probability at least $1 - \delta$ the graph $\tilde{G} = (V, \tilde{E}, \tilde{w})$ satisfies $L_G \approx_\epsilon L_{\tilde{G}}$ and $|\tilde{E}| \le O\left(n\epsilon^{-2}\log(n/\delta)\right)$.

The proof uses Bernstein bounds to prove the concentration of the constructed random graph.

## 7 Solving Laplacian Linear Equations Approximately

Idea: solving Laplacian linear equations requires $O(m)$, which is expensive when the graph is dense. By approximating the Laplacian, we can get an approximation of the solution quickly.

Given PSD matrix $M$ and $d \in \mathbf{im}(M)$, let $Mx^* = d$. We say that $\tilde{x}$ is an $\epsilon$-approximate solution to $Mx = d$ iff $\|\tilde{x} - x^*\|_M^2 \le \epsilon\|x^*\|_M^2$, where $\|x\|_M^2 = x^\top M x$. Note that any solution to $Mx = d$ has the same $\|\cdot\|_M^2$, as they differ by a vector in the kernel of $M$.

Theorem: Given a Laplacian $\boldsymbol{L}$ of a weighted undirected graph $G = (V, E, \boldsymbol{w})$ with $|E| = m$ and $|V| = n$ and a demand vector $\boldsymbol{d} \in \mathbb{R}^V$, we can find $\tilde{\boldsymbol{x}}$ that is an $\epsilon$-approximate solution to $\boldsymbol{Lx} = \boldsymbol{d}$, using an algorithm that takes time $O(m\log^c n \log(1/\epsilon))$ for some fixed constant $c$ and succeeds with probability

$1 - 1/n^{10}$. Note that without known Cholesky decomposition in advance, the exact solution requires $O(n^3)$ and $m \leq n^2/2$.