

Problem A. (Adopted from MIT EECS 6.S955)

Given a graph $G = (V, E)$, $V = \{1, \dots, n\}$, $E \subseteq V \times V$. A common problem is *graph layout*, where we choose positions of the vertices in V on the plane \mathbb{R}^2 respecting the connectivity of G . Assume that $(i, i) \notin E \ \forall i \in V$ and $(i, j) = (j, i) \ \forall (i, j) \in E$.

Take $\vec{v}_1, \dots, \vec{v}_n \in \mathbb{R}^2$ to be the positions of the vertices in V ; these are the unknowns in graph layout. Suppose a finite positions of vertices are specified in $V_0 \subseteq V$ (labeled as $\vec{v}_k^0 \ \forall k \in V_0$). Derive two linear systems satisfied by (x_i, y_i) of \vec{v}_i 's to minimize the Dirichlet energy:

$$\begin{aligned} \min E(\vec{v}_1, \dots, \vec{v}_n) &= \sum_{(i,j) \in E} \|\vec{v}_i - \vec{v}_j\|_2^2 \\ \text{s.t } \vec{v}_k &= \vec{v}_k^0 \quad \forall k \in V_0. \end{aligned}$$

Implement and compare both gradient descent and conjugate gradients for solving this system. Use a preconditioner of choice for conjugate gradients. Show improve of convergence.

Solution .

Since $\vec{v}_i \in \mathbb{R}^2$, let $\vec{v}_i = (x_i, y_i)$. This implies $\|\vec{v}_i - \vec{v}_j\|_2^2 = (x_i - x_j)^2 + (y_i - y_j)^2$. Then

$$\begin{aligned} E(\vec{v}_1, \dots, \vec{v}_n) &= \sum_{(i,j) \in E} \|\vec{v}_i - \vec{v}_j\|_2^2 \\ &= \sum_{(i,j) \in E} (x_i - x_j)^2 + (y_i - y_j)^2 \\ &= E_x + E_y \quad \text{where } \begin{cases} E_x \equiv \sum_{(i,j) \in E} (x_i - x_j)^2 \\ E_y \equiv \sum_{(i,j) \in E} (y_i - y_j)^2 \end{cases} \end{aligned}$$

Rewriting our objective

$$\begin{aligned} \min E_x + E_y \\ \text{s.t } (x_k, y_k) &= \vec{v}_k = \vec{v}_k^0 \quad \forall k \in V_0. \end{aligned}$$

We solve for E_x . Define $U = V \setminus V_0$. Then

$$\min \sum_{(i,j) \in E} (x_i - x_j)^2 \equiv \min \sum_{(i,u) \in E} (x_u - x_i)^2 \quad \forall u \in U$$

$$\frac{\partial E_x}{\partial x_u} = 2 \sum_{i \in N(u)} (x_u - x_i) = 0$$

$$\iff \sum_{i \in N(u)} (x_u - x_i) = 0$$

$$\iff \delta(u)x_u - \sum_{i \in N(u)} x_i = 0$$

$$\iff \delta(u)x_u - \sum_{i \in N(u) \cap U} x_i = \sum_{j \in N(u) \cap V_0} x_j$$

Denote the cardinality of U as $m = |U|$. Let

$$1. \ L \in \mathbb{R}^{m \times m}; \ L_{ii} = \delta(i); \ L_{ij} = \begin{cases} -1 & \forall i \in N(j) \text{ for } j \in U \\ 0 & \text{otherwise} \end{cases} \quad (\text{the Laplacian matrix})$$

$$2. \vec{x} \in \mathbb{R}^{m \times 1} = (x_{u_1}, \dots, x_{u_m})^\top \quad \forall u \in U$$

$$3. \vec{b}_x \in \mathbb{R}^{m \times 1} = (x_{j_1}, \dots, x_{j_m})^\top \quad \forall j \in N(i) \cap V_0 \text{ with } i \in U$$

This defines a linear system $E_x \equiv L\vec{x} - \vec{b}_x$. The work for E_y is analogous.

With our assumption $(i, j) = (j, i) \quad \forall (i, j) \in E$, L is intuitively symmetric. Also, the Laplacian graph matrix is always (strictly or not) diagonally dominant with non-negative diagonal entries. These combined guarantees positive semi-definiteness.

Complexity

The method of both steepest descent and conjugate gradients both depends on the matrix-vectors products operations. More often, the graph Laplacian matrix is sparse. Let t be the number of non-zero entries of L . [1] Then the complexity of:

- Gradient descent: $O(t\kappa)$
- Conjugate gradients: $O(t\sqrt{\kappa})$

with $\kappa \equiv \text{cond}(L)$.

Preconditioning

Let us decompose $L = D + A + A^\top$ where D is the diagonal matrix consists of the diagonal values of L , A is the strictly lower triangular matrix consists of corresponding part of L . Then, the SOR iterative scheme is

$$(\omega^{-1}D + A)x_{k+1}^\rightarrow = ((\omega^{-1} - 1)D - A^\top)x_k^\rightarrow + \vec{b}_x$$

for some constant $\omega \in (0, 2)$.

Show of convergence.

By simply letting $M \equiv (\omega D + A)$ and $N \equiv ((\omega^{-1} - 1)D - A^\top)$ yields the classic Jacobi's iterative scheme

$$Mx_{k+1}^\rightarrow = Nx_k^\rightarrow + \vec{b}_x$$

which converges to $L^{-1}\vec{b}_x$ when $\rho(M^{-1}N) < 1$.

Improve of convergence.

show later

■

References

- [1] J. R. Shewchuk, "An introduction to the conjugate gradient method without the agonizing pain," tech. rep., USA, 1994.