# Graph Drawing using the Laplacian Based on Speilamn, Chapter 3

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#### Overview

- 1 Embedding a graph into the line
- 2 One dimensional artwork
- 3 Embedding a graph into the plane
- 4 Two dimensional artwork
- 5 Three dimensional artwork

### Embedding a graph to $\mathbb{R}$

$$X: V \longrightarrow \mathbb{R}$$

Say we wish to embed a graph G to the reals. How should we go about it? Connected vertices should be close, so we can express this as minimizing

$$\mathbf{x}^T \mathbf{L} \mathbf{x} = \sum_{uv \in E} (\mathbf{x}(u) - \mathbf{x}(v))^2,$$

where  $\mathbf{x}$  is the embedding.

#### Question

What is the obvious issue with this suggestion?

### Embedding a graph to $\mathbb R$



So we normalize so that the points in  ${\bf x}$  are not too concentrated around any point.

$$\forall p \in \mathbb{R} \quad \sum_{v \in V} (\mathsf{x}(v) - p)^2 \geq 1.$$

#### Question

What can we say about p?

### Embedding a graph to $\mathbb R$

So we normalize so that the points in  $\mathbf{x}$  are not too concentrated around a point.

$$\forall p \in \mathbb{R} \quad \sum_{v \in V} (\mathbf{x}(v) - p)^2 \geq 1.$$

$$p = \mathbb{E}_{v} \mathbf{x}(v) = \mathbf{u}^{T} \mathbf{x}$$

where  $\mathbf{u} = \frac{1}{n} \cdot \mathbf{1}$ . By shifting, we may as well assume  $\mathbf{u}^T \mathbf{x} = 0$ .

### Embedding a graph to $\mathbb R$

Hence, we want to minimize  $\mathbf{x}^T \mathbf{M} \mathbf{x}$  subject to  $\mathbf{u}^T \mathbf{x} = 0$  and  $\|\mathbf{x}\|_2 = 1$ .

#### Question

Who is x?



Figure: 20-vertex path graph embedded into  $\mathbb{R}$ .

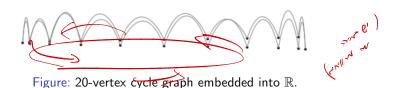


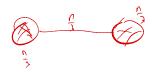


Figure: Depth-4 complete binary tree embedded into  $\mathbb{R}$ .





Figure: Third-dumbbell embedded into  $\mathbb{R}$ .



$$\sum_{uv} \left( \chi(u) - \chi(v) \right)^{2}$$

Figure: 5-clique embedded into  $\mathbb{R}$ .

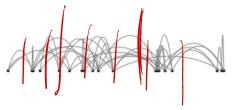


Figure: Degree 2 plus symmetrization random graph embedded into  $\mathbb{R}$ .

## My modest code

```
using LinearAlgebra
using Plots
using Luxor
function draw_on_line(M)
    n = size(M)[1]
    E = eigen(M)
    v2 = E.vectors[:,n-1]
    s = 300
    @png begin
        for i in 1:n
            circle(Point(s*v2[i],0),2,:fill)
        end
        sethue("gray")
        setline(1)
        for i in 1:n
            for j in i:n
                if (M[i,i] == 1)
                    A = Point(s*v2[i]. 0)
                    B = Point(s*v2[j], 0)
                    C = Point((A.x+B.x)/2,-80+rand(-40:1:40))
                    curve(A, C, B)
                    strokepath()
                end
           end
       end
    end
end
P = clique_no_loops(10)
```

### Drawing a graph on the plane

Moving to two dimensions, we now wish to find a pair  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ that minimizes

$$\sum_{uv \in E} \left\| \begin{pmatrix} \mathbf{x}(u) \\ \mathbf{y}(u) \end{pmatrix} - \begin{pmatrix} \mathbf{x}(v) \\ \mathbf{y}(v) \end{pmatrix} \right\|_{2}^{2}$$
subject to  $\mathbf{u}^{T}\mathbf{x} = \mathbf{u}^{T}\mathbf{y} = 0$  and  $\|\mathbf{x}\| = \|\mathbf{y}\| = 1$ .
$$(1) = \mathbf{x}^{T}\mathbf{L}\mathbf{x} + \mathbf{y}^{T}\mathbf{L}\mathbf{y}$$

$$(2) \mathbf{x}^{T}\mathbf{L}\mathbf{y}^{T}\mathbf{x} + \mathbf{y}^{T}\mathbf{L}\mathbf{y}$$

$$(3) \mathbf{x}^{T}\mathbf{y}^{T}\mathbf{y} = 0$$

$$(4) \mathbf{x}^{T}\mathbf{y}^{T}\mathbf{y} = 0$$

$$(5) \mathbf{x}^{T}\mathbf{y}^{T}\mathbf{y} = 0$$

$$(7) \mathbf{y}^{T}\mathbf{y} = 0$$

$$(8) \mathbf{y}^{T}\mathbf{y} = 0$$

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$$(8) \mathbf{y}^{T}\mathbf{y} = 0$$

$$(9) \mathbf{y$$

#### Question

What other condition you would suggest we include?

This is precisely Hall's idea.

$$x^Ty = 0$$

### A lower bound

#### **Theorem**

Let **L** be a Laplacian matrix. For  $k \ge 1$  let  $\mathbf{x}_1, \dots, \mathbf{x}_k$  be orthonormal vectors that are all orthogonal to **1**. Then,

$$\sum_{i=1}^k \mathbf{x}_i^T \mathbf{L} \mathbf{x}_i \ge \sum_{i=2}^{k+1} \lambda_i.$$

## Some room for the proof

$$\begin{array}{ll}
x_{i} = \sum_{j=1}^{n} \lambda_{j} \left( \psi_{j}^{T} x_{i} \right)^{2} \\
x_{i} = \sum_{j=1}^{n} \lambda_{j} \left( \psi_{j}^{T} x_{i} \right)^{2} \\
&= \sum_{j=1}^{n} \left( \lambda_{j}^{T} - \lambda_{k+1} \right) \left( \psi_{j}^{T} x_{i} \right)^{2} \\
&= \sum_{j=1}^{n} \left( \psi_{j}^{T} x_{i} \right)^{2} \\
&= \lambda_{k+1} + \sum_{j=1}^{n} \left( \lambda_{j}^{T} - \lambda_{k+1} \right) \left( \psi_{j}^{T} x_{i} \right)^{2} \\
&= \lambda_{k+1} + \sum_{j=1}^{n} \left( \lambda_{j}^{T} - \lambda_{k+1} \right) \sum_{j=1}^{n} \left( \psi_{j}^{T} x_{i} \right)^{2} \\
&= \lambda_{k+1} + \sum_{j=1}^{n} \left( \lambda_{j}^{T} - \lambda_{k+1} \right) \sum_{j=1}^{n} \left( \psi_{j}^{T} x_{i} \right)^{2} \\
&= \lambda_{k+1} + \sum_{j=1}^{n} \left( \lambda_{j}^{T} - \lambda_{k+1} \right) \sum_{j=1}^{n} \left( \psi_{j}^{T} x_{i} \right)^{2}
\end{array}$$



### AN r-DIMENSIONAL QUADRATIC PLACEMENT ALGORITHM\*

#### KENNETH M. HALL†

State of California, Department of General Services

In this paper the solution to the problem of placing n connected points (or nodes) in r-dimensional Euclidean space is given. The criterion for optimality is minimizing a weighted sum of squared distances between the points subject to quadratic constraints of the form X'X = 1, for each of the r unknown coordinate vectors. It is proved that the problem reduces to the minimization of a sum or r positive semi-definite quadratic forms which, under the quadratic constraints, reduces to the problem of finding reigenvectors of a special "disconnection" matrix. It is shown, by example, how this can serve as a basis for cluster identification.

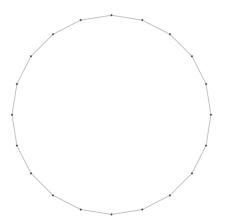


Figure: 20-cycle embedded into  $\mathbb{R}^2$ .

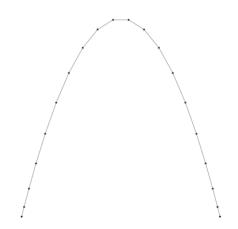


Figure: 20-vertex path embedded into  $\mathbb{R}^2$ .

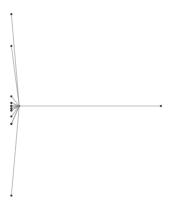


Figure: 20-vertex star graph embedded into  $\mathbb{R}^2$ .

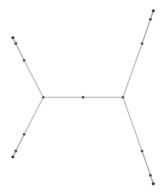


Figure: Depth-4 complete binary tree embedded into  $\mathbb{R}^2$ .

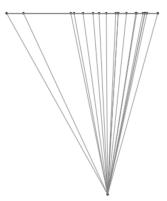


Figure: 20-vertex clique embedded into  $\mathbb{R}^2$ .

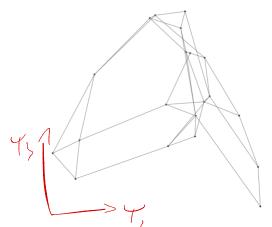


Figure: 20-vertex random graph (degree 2 symmetrized) embedded into  $\mathbb{R}^2$ .

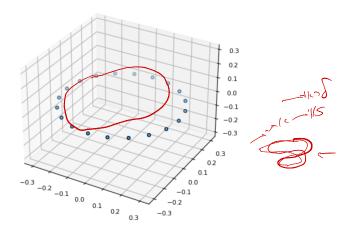


Figure: 20-cycle embedded into  $\mathbb{R}^3$ .

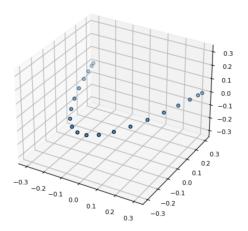


Figure: 20-vertex path embedded into  $\mathbb{R}^3$ .

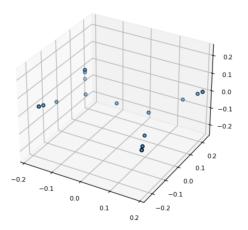


Figure: Depth-4 complete binary tree embedded into  $\mathbb{R}^3$ .

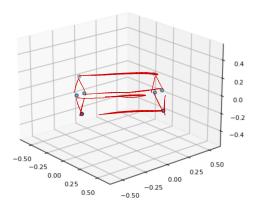


Figure: Who am I?

### My modest code

```
function draw3d(M)
    n = size(M)[1]
    E = eigen(M)
    v2 = E.vectors[:,n-1]
    v3 = E.vectors[:,n-2]
    v4 = E.vectors[:,n-3]
    Plots.scatter(v2, v3, v4, leg = false, camera = (50,20))
end
draw3d(lap(cube()))
```