

# La Théorie Spectrale des Graphes

(Spectral (Graph Theory)), not ~~((spectral graph) theory)~~

Croix Gyurek

April 27, 2022

Introduction

Why It Matters

Drawing Graphs

Why Does This Work?

References

# Matrix Definitions

- ▶ Graph  $G = (V, E)$  where  $V = \{v_1, \dots, v_n\}$  has 2 associated matrices, Adjacency and Laplacian

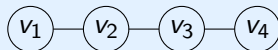
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Example: 4-path



$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

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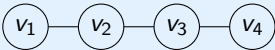
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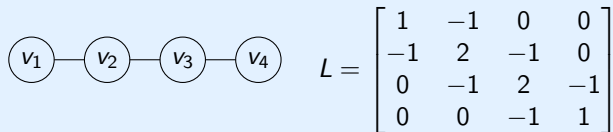
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- ▶ Notice rows and columns of  $L$  sum to 0.

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- ▶ Spectral Theorem: both  $A$  and  $L$  have an orthonormal basis ( $n$  mutually orthogonal eigenvectors) since they're symmetric

# Useful Product Identities

Both  $A$  and  $L$  play nice with dot products. For  $\mathbf{v} \in \mathbb{R}^n$ :

$$\mathbf{v} \cdot A\mathbf{v} = \sum_{(i,j) \in E} v_i v_j$$

$$\mathbf{v} \cdot L\mathbf{v} = \sum_{(i,j) \in E} (v_i - v_j)^2$$

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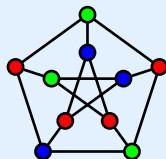
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- ▶  $\lambda_1 = 0$ ; multiplicity of  $0 = \#$  connected components of  $G$ 
  - ▶  $L\mathbb{1} = 0$

## More Classical Graph Theory

**Chromatic number**  $\chi(G) = \min \#$  of colors for vertices so no same-color vertices share an edge



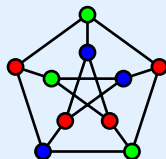
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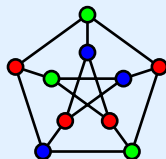
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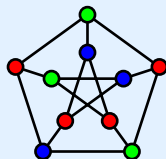
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Independence number:  $\text{ind } G \leq n \left( 1 - \frac{d_{min}}{\lambda_{max}} \right)$

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- ▶ Eigenvectors of  $L$  can give nice pictures

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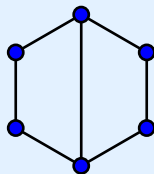
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4. Use  $j$ -th coordinate of each  $v$ : vertex  $j$  goes at  $(v_{2,j}, v_{3,j})$ .

## Example: 6-cycle with an extra edge

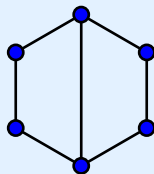
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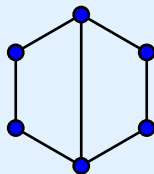
Eigenvalues: 0, 1, 2, 3, 3, 5. Eigenvectors:

$$v_2 = \left(-\frac{1}{2}, 0, \frac{1}{2}, \frac{1}{2}, 0, -\frac{1}{2}\right)^T \text{ and}$$

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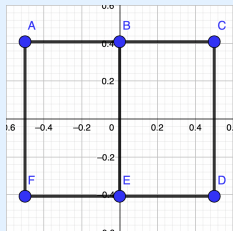
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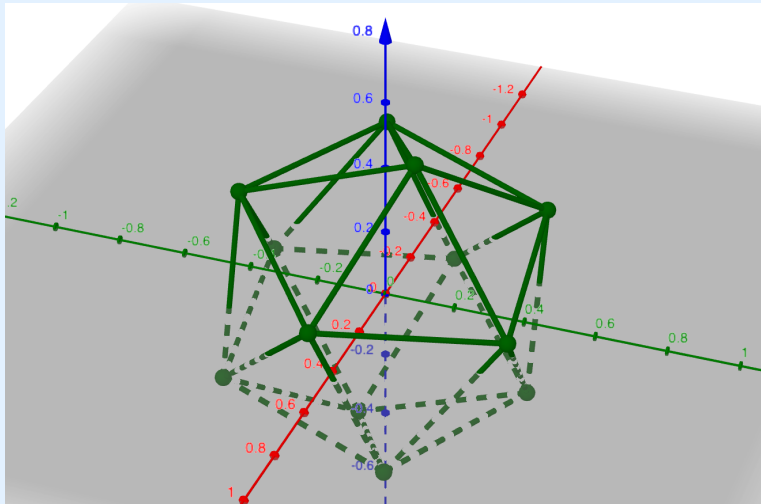
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- ▶ So let's use the coordinates of  $\mathbf{v}_2, \mathbf{v}_3, \mathbf{v}_4$ .

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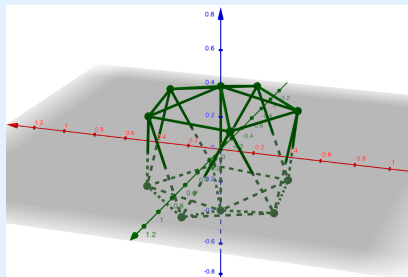
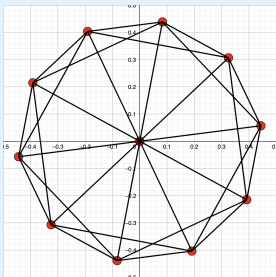
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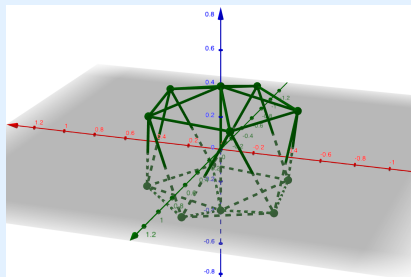
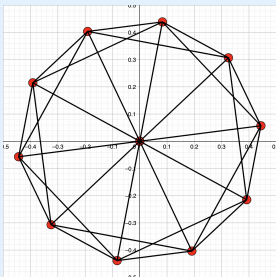
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Notice the icosahedron is squished a bit!

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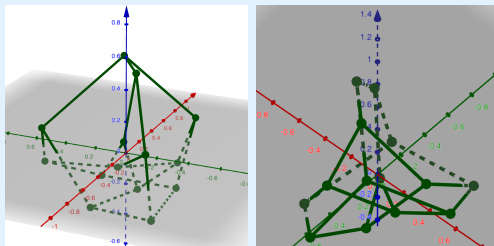


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- ▶ This means the Fano plane graph is naturally six-dimensional!

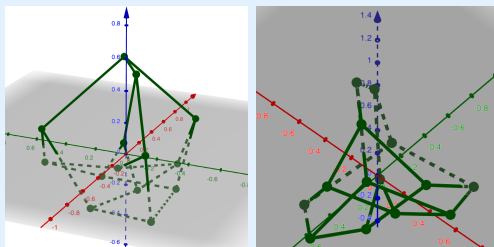


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The eigenvectors  $\mathbf{v}_k$  are solutions.

## Basic Idea: The One-Dimensional Case

Suppose we want to “draw”  $G$  on a line.

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- ▶ Trivial solution:  $x_j \equiv 1/\sqrt{n}$ . Let's enforce  $\sum_j x_j = 0$ .



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- ▶ So we’re minimizing  $\mathbf{x} \cdot L\mathbf{x}$  subject to  $\mathbf{x} \perp \mathbf{1}$  and  $\|\mathbf{x}\| = 1$ .
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Similarly, requiring  $\mathbf{x} \perp \mathbf{y}$  gives  $\mathbf{y} = \mathbf{v}_3$ , etc.

## References

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