

# Graph Partitioning II: Spectral Methods

<b>Class</b>	Algorithmic Methods of Data Mining
<b>Program</b>	M. Sc. Data Science
<b>University</b>	Sapienza University of Rome
<b>Semester</b>	Fall 2015
<b>Lecturer</b>	Carlos Castillo <a href="http://chato.cl/">http://chato.cl/</a>

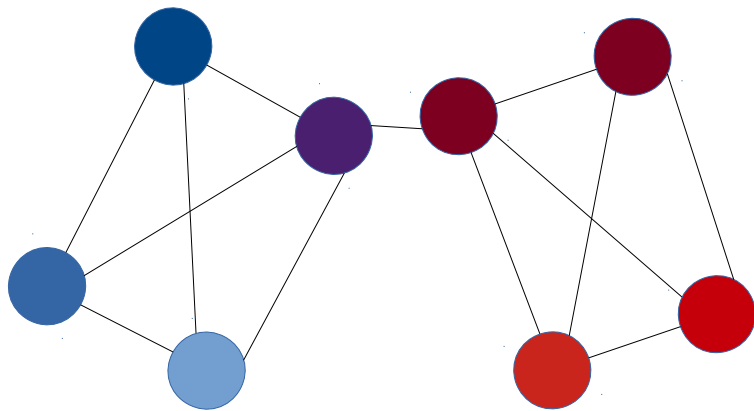
## Sources:

- Evimaria Terzi: “Clustering: graph cuts and spectral graph partitioning” [[link](#)]
- Daniel A. Spielman: “The Laplacian” [[link](#)]
- Jure Leskovec: “Defining the graph laplacian” [[link](#)]

# Graph projections

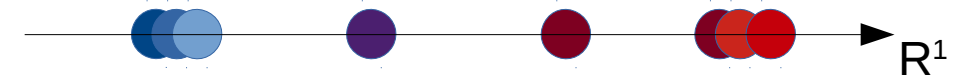
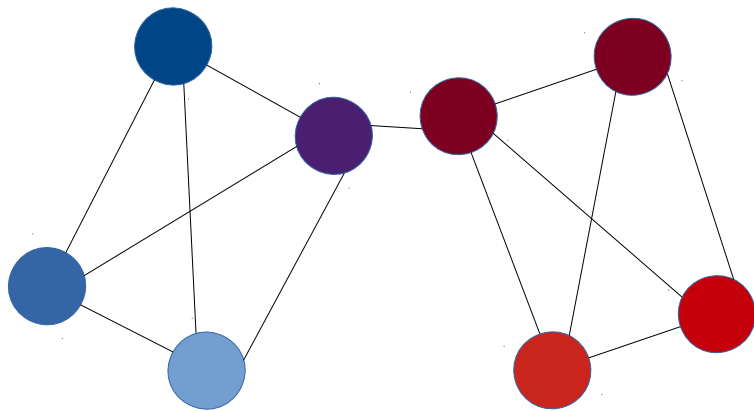
# Graphs are nice, but ...

- They describe only local relationships
- We would like to understand a global structure
- Our objective is transforming a graph into a more familiar object: a cloud of points in  $\mathbb{R}^k$



# Graphs are nice, but ...

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Distances should be somehow preserved

# Simple 3D graph projection

- Start a BFS from a random node, that has  $x=1$ , and nodes visited have ascending  $x$
- Start a BFS from another random node, which has  $y=1$ , and nodes visited have ascending  $y$
- Start a BFS from yet another node, which has  $z=1$ , and nodes visited have ascending  $z$
- Project node  $n$  to position  $(x_n, y_n, z_n)$

*How do you think this works in practice?*

# Eigenvectors of adjacency matrix

# Adjacency matrix of $G=(V,E)$

- Matrix of size  $|V| \times |V|$  such that:

$$A_{ij} = \begin{cases} 1 & \text{if } (i, j) \in E \\ 0 & \text{otherwise} \end{cases}$$

- What is  $Ax$ ? Think of  $x$  as a set of labels/values:

$$\begin{bmatrix} a_{11} & \dots & a_{1n} \\ a_{21} & \dots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

$$y_i = \sum_{j:(j,i) \in E} x_j$$

$Ax$  is a vector whose  $i^{\text{th}}$  coordinate contains the sum of the  $x_j$  who are in-neighbors of  $i$

# Properties of adjacency matrix

$$A_{ij} = \begin{cases} 1 & \text{if } (i, j) \in E \\ 0 & \text{otherwise} \end{cases}$$

- How many non-zeros are in every row of A?

$$\begin{bmatrix} a_{11} & \dots & a_{1n} \\ a_{21} & \dots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix}$$



# Understanding the adjacency matrix

$$A_{ij} = \begin{cases} 1 & \text{if } (i, j) \in E \\ 0 & \text{otherwise} \end{cases}$$

What is  $Ax$ ? Think of  $x$  as a set of labels/values:

$$\begin{bmatrix} a_{11} & \dots & a_{1n} \\ a_{21} & \dots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

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# Spectral graph theory

- The study of the eigenvalues and eigenvectors of a graph matrix  $Ax = \lambda x$ 
  - Adjacency matrix
  - Laplacian matrix (next)
- Suppose graph is  $d$ -regular (every node has degree  $d$ ), what is the value of:

$$\begin{bmatrix} a_{11} & \dots & a_{1n} \\ a_{21} & \dots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} = ?$$

# An easy eigenvector of A

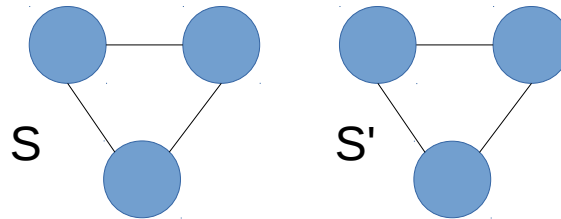
- Suppose graph is  $d$ -regular, i.e. all nodes have degree  $d$ :

$$\begin{bmatrix} a_{11} & \dots & a_{1n} \\ a_{21} & \dots & a_{2n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} d \\ d \\ \vdots \\ d \end{bmatrix}$$

- So  $[1, 1, \dots, 1]^\top$  is an eigenvector of eigenvalue  $d$

# Disconnected graphs

- Suppose graph is disconnected (still regular)

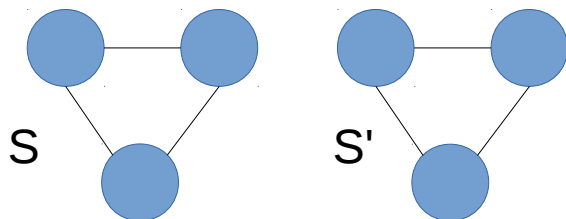


- Then matrix has block structure:

$$A = \begin{bmatrix} S & 0 \\ 0 & S' \end{bmatrix}$$

# Disconnected graphs

- Suppose graph is disconnected (still regular)

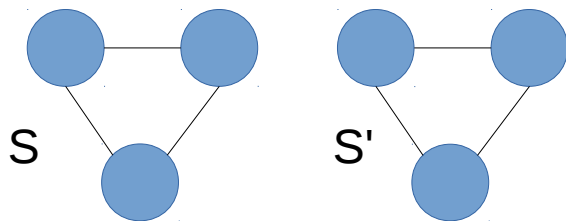


$$\text{Let } x_i^S = \begin{cases} 1 & \text{if } i \in S \\ 0 & \text{if } i \in S' \end{cases}$$

$$\begin{bmatrix} S & 0 \\ 0 & S' \end{bmatrix} \begin{bmatrix} 1 \\ \vdots \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = ?$$

# Disconnected graphs

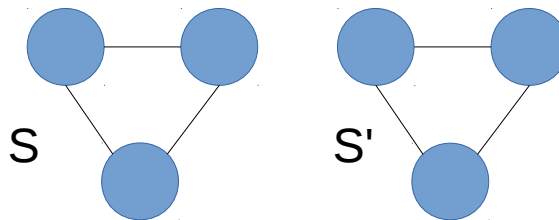
- Suppose graph is disconnected (still regular)



$$\text{Let } x_i^S = \begin{cases} 1 & \text{if } i \in S \\ 0 & \text{if } i \in S' \end{cases} \quad \begin{bmatrix} S & 0 \\ 0 & S' \end{bmatrix} \begin{bmatrix} 1 \\ \vdots \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} d \\ \vdots \\ d \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

# Disconnected graphs

- Suppose graph is disconnected (still regular)



$$Ax^S = dx^S$$

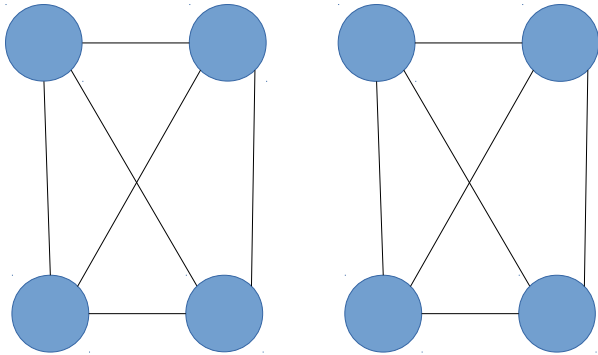
$$Ax^{S'} = dx^{S'}$$

- *What happens if there are more than 2 connected components?*

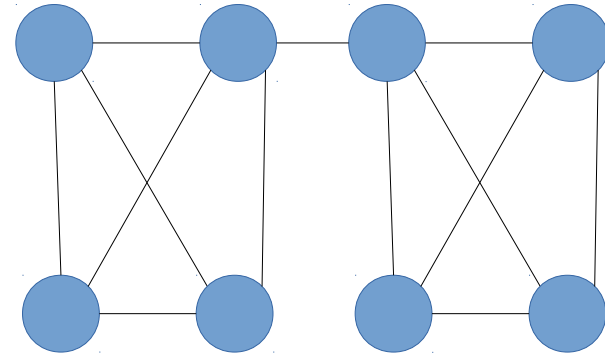
# In general

Disconnected graph

*Almost* disconnected graph



$$\lambda_1 = \lambda_2$$



$$\lambda_1 \approx \lambda_2$$

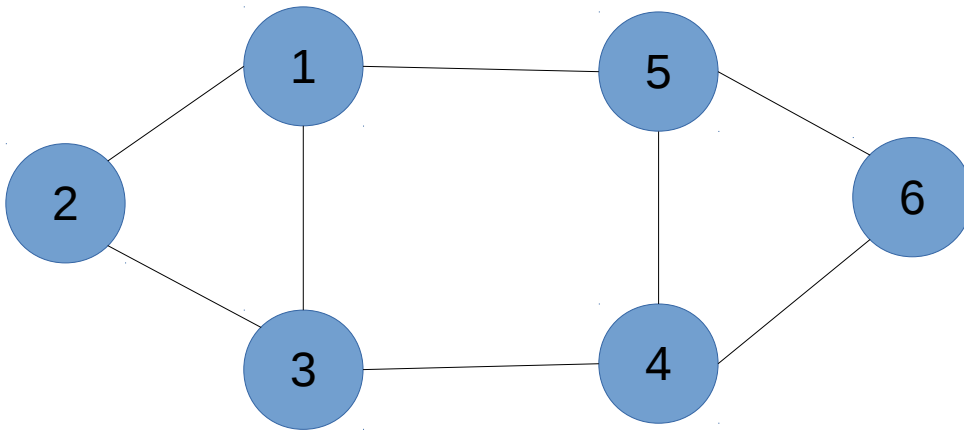
Small “eigengap”



# Graph Laplacian

# Adjacency matrix

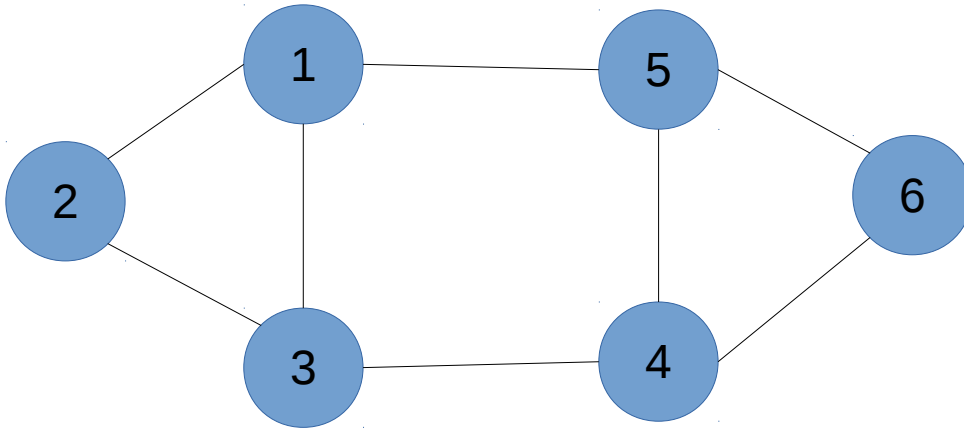
$$A_{ij} = \begin{cases} 1 & \text{if } (i, j) \in E \\ 0 & \text{otherwise} \end{cases}$$



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

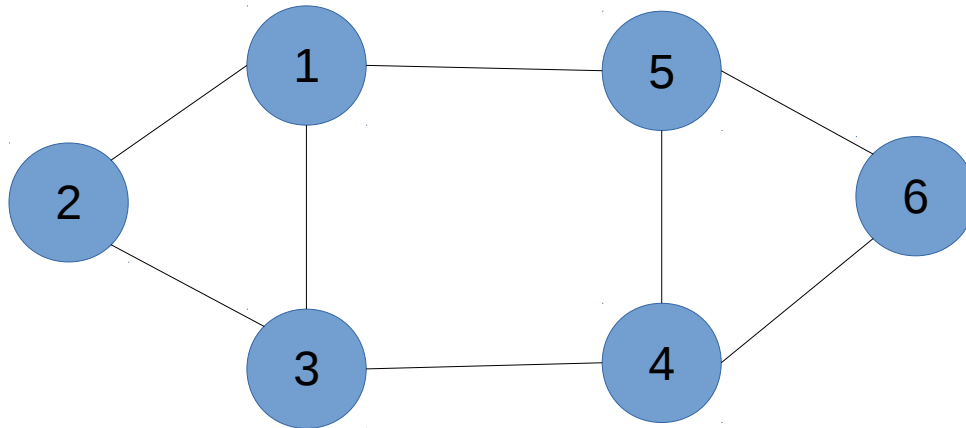
# Degree matrix

$$D_{ij} = \begin{cases} d(i) & \text{if } i = j \\ 0 & \text{otherwise} \end{cases}$$



$$D = \begin{bmatrix} 3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 \end{bmatrix}$$

# Laplacian matrix



$$L = D - A$$

$$L = \begin{bmatrix} 3 & -1 & -1 & 0 & -1 & 0 \\ -1 & 2 & -1 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & 0 & 0 & -1 & 3 & -1 \\ 0 & 0 & 0 & -1 & -1 & 2 \end{bmatrix}$$

# Laplacian matrix $L = D - A$

- Symmetric
- Eigenvalues non-negative and real
- Eigenvectors real and orthogonal

$$L\vec{1} = \begin{bmatrix} 3 & -1 & -1 & 0 & -1 & 0 \\ -1 & 2 & -1 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & 0 & 0 & -1 & 3 & -1 \\ 0 & 0 & 0 & -1 & -1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = ?$$

# Constant vector is eigenvector of L

- The constant vector  $x=[1,1,\dots,1]^T$  is again an eigenvector, but this time has eigenvalue 0

$$Lx = \begin{bmatrix} 3 & -1 & -1 & 0 & -1 & 0 \\ -1 & 2 & -1 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 \\ 0 & 0 & -1 & 3 & -1 & -1 \\ -1 & 0 & 0 & -1 & 3 & -1 \\ 0 & 0 & 0 & -1 & -1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} = 0x$$

# If the graph is disconnected

- If there are two connected components, the same argument as for the adjacency matrix applies, and  $\lambda_1 = \lambda_2 = 0$
- In general, the multiplicity of eigenvalue 0 is the number of connected components

$$x^T L x$$



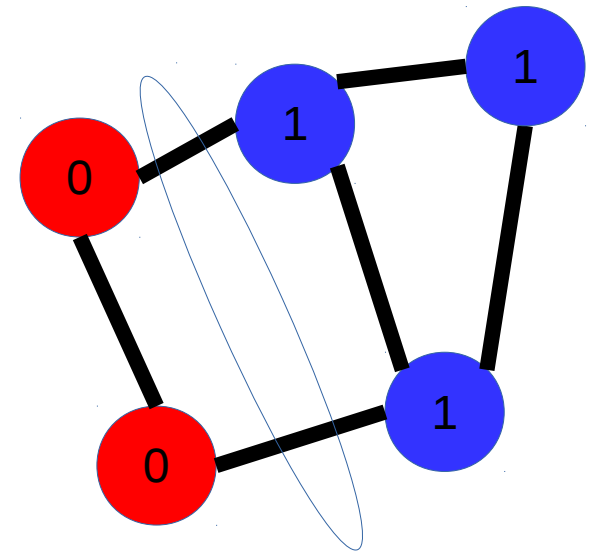
# Important property of $x^T L x$

$$\begin{aligned}x^T L x &= \sum_{i=1}^n \sum_{j=1}^n L_{ij} x_i x_j \\&= \sum_{i=1}^n \sum_{j=1}^n (D_{ij} - A_{ij}) x_i x_j \\&= \sum_{i=1}^n D_{ii} x_i^2 - \sum_{(i,j) \in E} 2x_i x_j \\&= \sum_{(i,j) \in E} x_i^2 + x_j^2 - 2x_i x_j = \sum_{(i,j) \in E} (x_i - x_j)^2\end{aligned}$$

Think of this quantity as the “stress” produced by the assignment of node labels  $x$

# $x^T L x$ and graph cuts

- Suppose  $(S, S')$  is a cut of graph  $G$
- Set  $x_i = \begin{cases} 1 & \text{if } i \in S \\ 0 & \text{if } i \in S' \end{cases}$



$$|c(S, S')| = 2$$

$$x^T L x = \sum_{(i,j) \in E} (x_i - x_j)^2 = \sum_{(i,j) \in c(S, S')} 1^2 = |c(S, S')|$$

# For symmetric matrices

- Important fact for symmetric matrices

$$\lambda_2 = \min_x \frac{x^T M x}{x^T x}$$

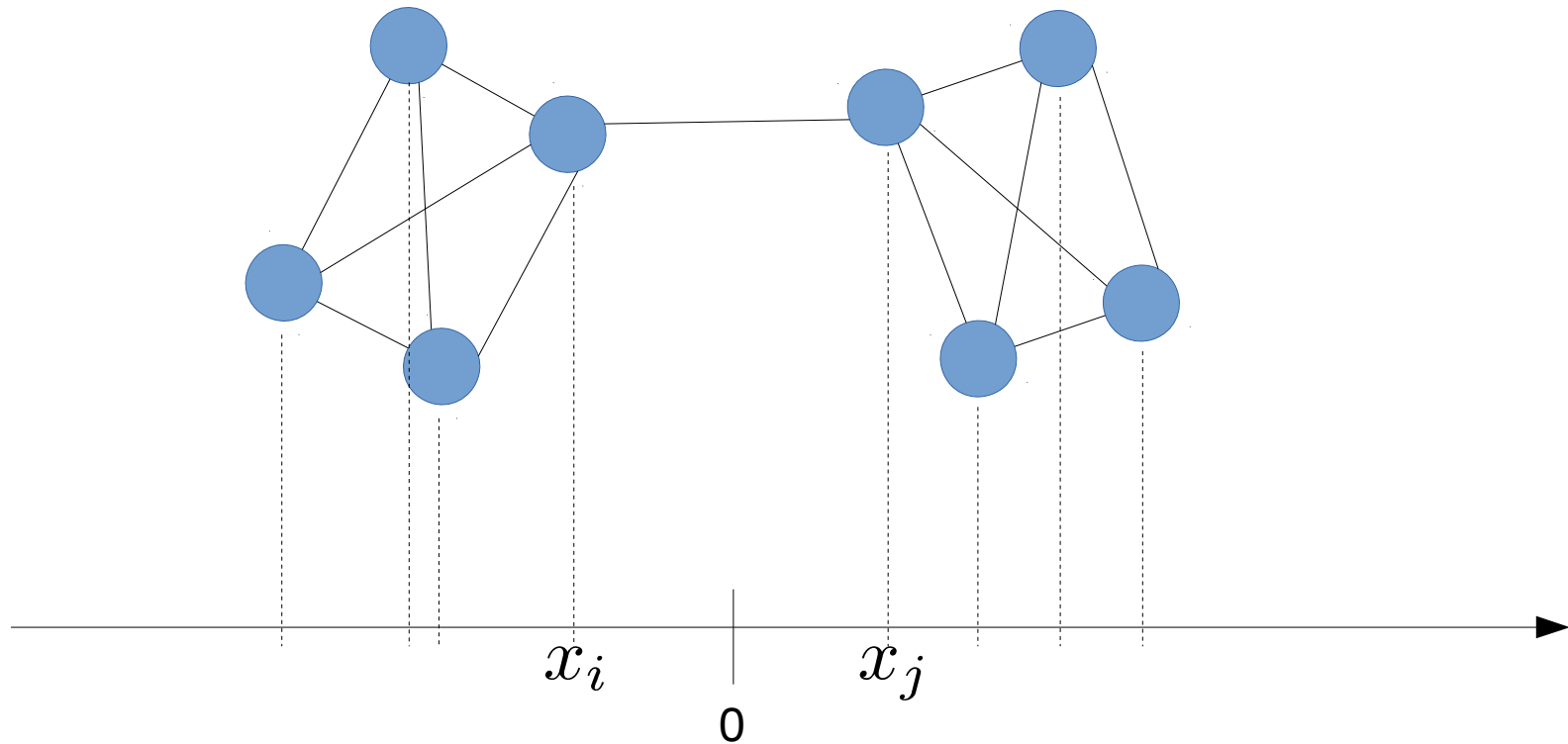
# Second eigenvector

- Orthogonal to the first one:  $x \cdot \vec{1} = 0 \Rightarrow \sum_i x_i = 0$
- Normal:  $\sum_i x_i^2 = 1$

$$\lambda_2 = \min_x \frac{x^T L x}{x^T x} = \min_{x: \sum x_i = 0} \frac{x^T L x}{\sum x_i^2} = \min_{x: \sum x_i = 0} \sum_{(i,j) \in E} (x_i - x_j)^2$$

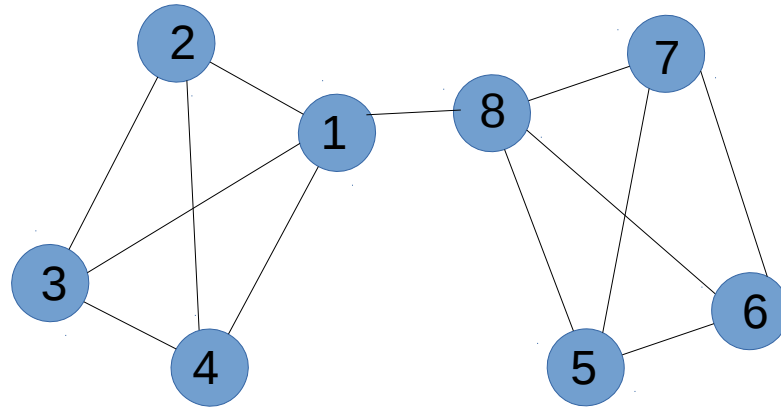
# What does this mean?

$$\lambda_2 = \min_{x: \sum x_i = 0} \sum_{(i,j) \in E} (x_i - x_j)^2$$



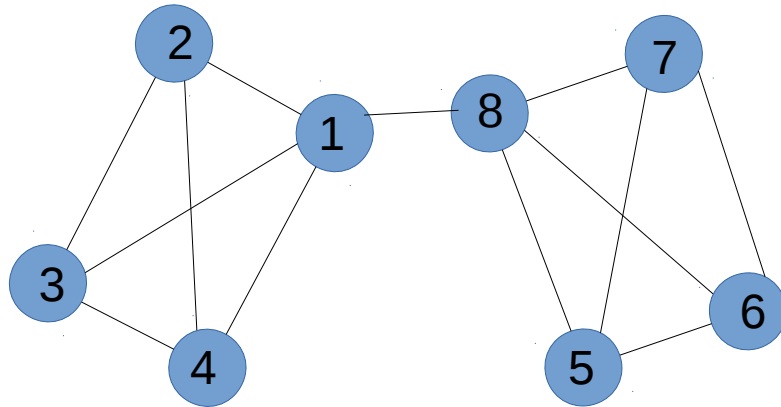
Nodes should be placed at both sides of 0 because  $\sum x_i = 0$

# Example Graph 1



$$L = \begin{bmatrix} 4 & -1 & -1 & -1 & 0 & 0 & 0 & -1 \\ -1 & 3 & -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & -1 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & -1 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & 3 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & -1 & 3 & -1 \\ -1 & 0 & 0 & 0 & -1 & -1 & -1 & 4 \end{bmatrix}$$

# Example Graph 1

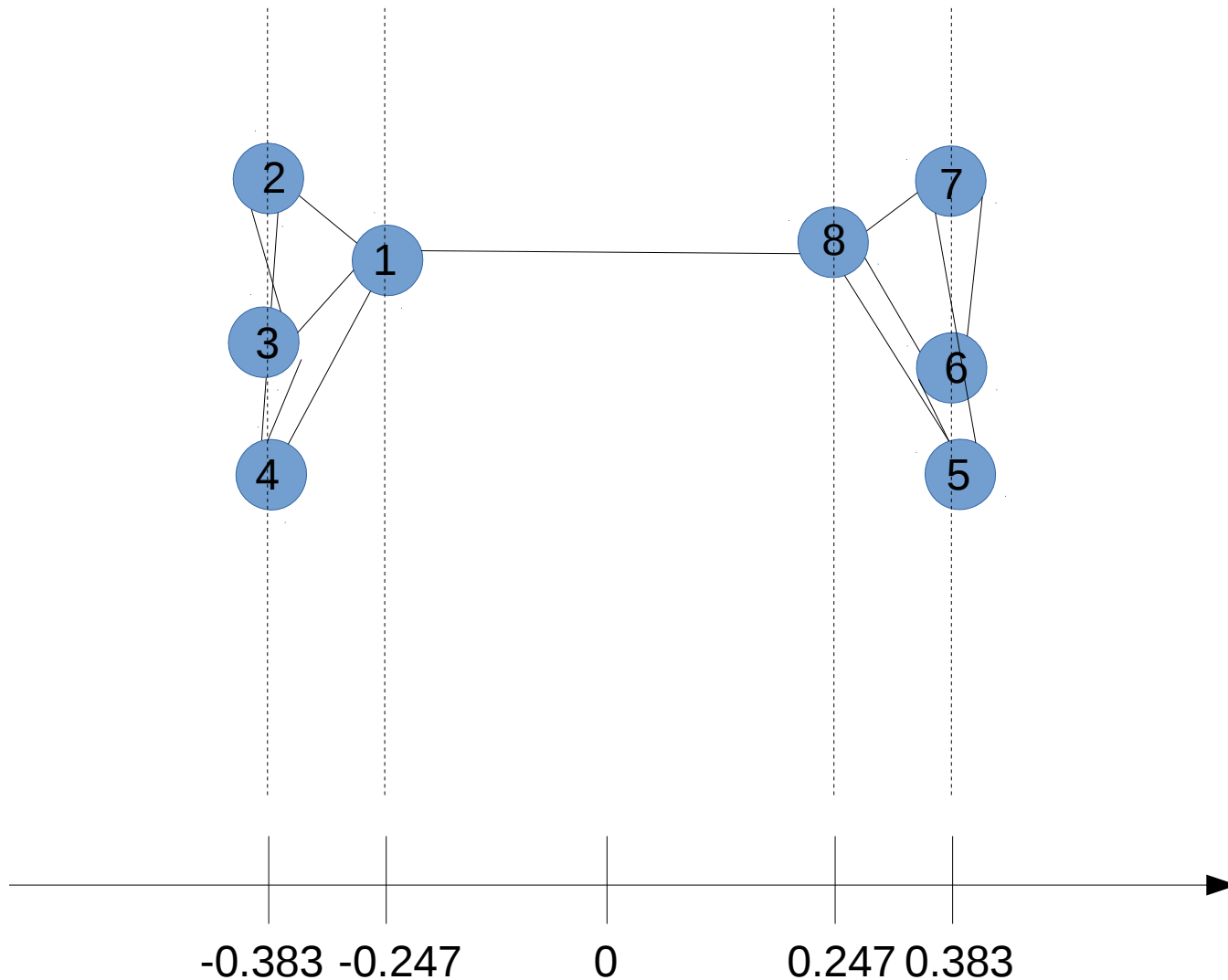


$$\lambda_1 = 0$$

$$\lambda_2 = 0.354$$

$$L = \begin{bmatrix} 4 & -1 & -1 & -1 & 0 & 0 & 0 & -1 \\ -1 & 3 & -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & -1 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & -1 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & 3 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & -1 & 3 & -1 \\ -1 & 0 & 0 & 0 & -1 & -1 & -1 & 4 \end{bmatrix} \quad v_2 = \begin{bmatrix} 0.247 \\ 0.383 \\ 0.383 \\ 0.383 \\ -0.383 \\ -0.383 \\ -0.383 \\ -0.247 \end{bmatrix}$$

# Example Graph 1, projected



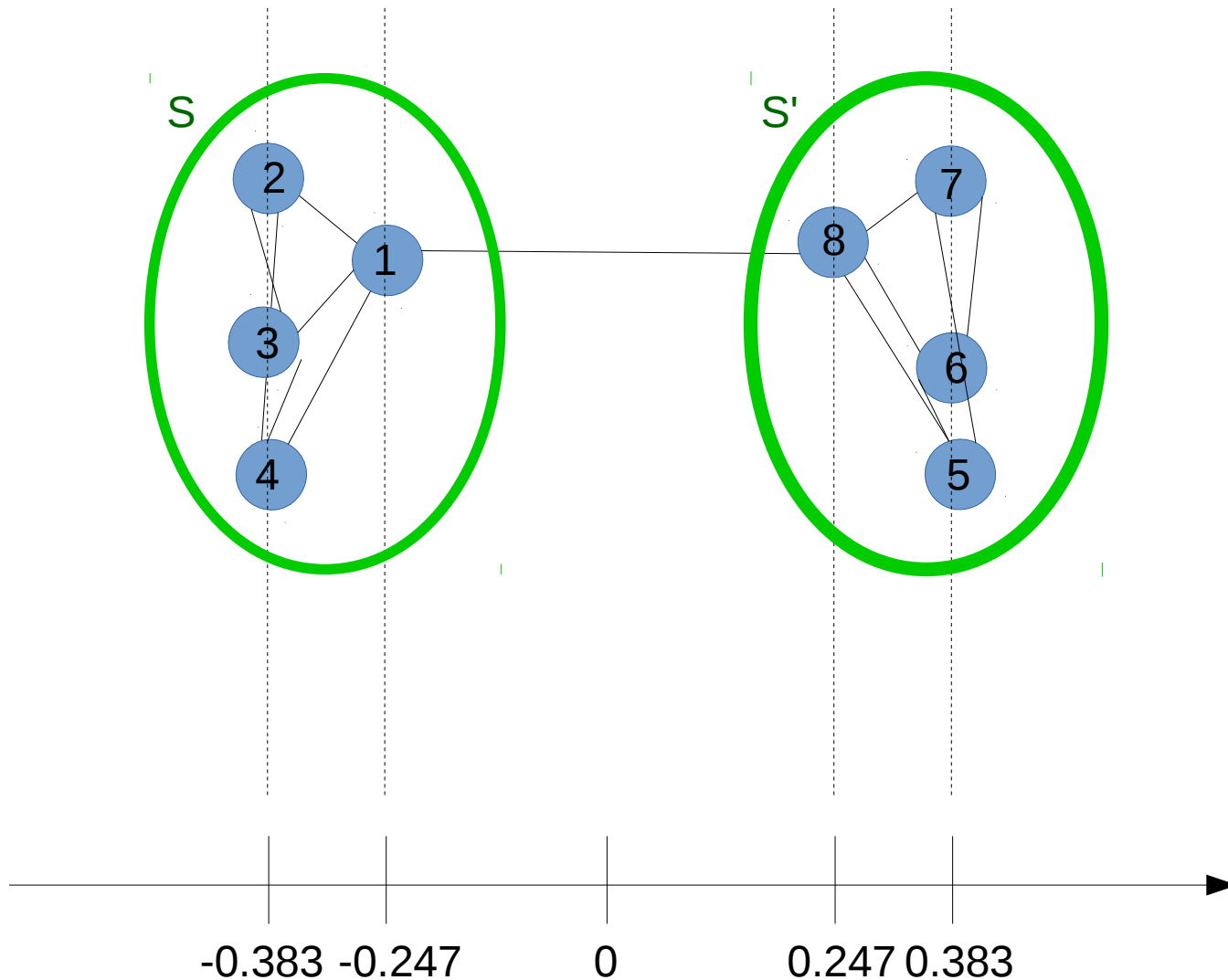
$$\lambda_1 = 0$$

$$\lambda_2 = 0.354$$

$$v_2 = \begin{bmatrix} 0.247 \\ 0.383 \\ 0.383 \\ 0.383 \\ -0.383 \\ -0.383 \\ -0.383 \\ -0.247 \end{bmatrix}$$



# Example Graph 1, communities



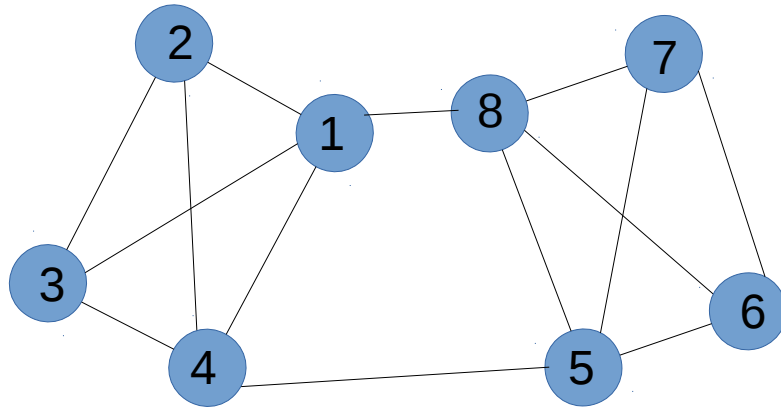
$$\lambda_1 = 0$$

$$\lambda_2 = 0.354$$

$$v_2 =$$

$$\begin{bmatrix} 0.247 \\ 0.383 \\ 0.383 \\ 0.383 \\ -0.383 \\ -0.383 \\ -0.383 \\ -0.247 \end{bmatrix}$$

# Example Graph 2

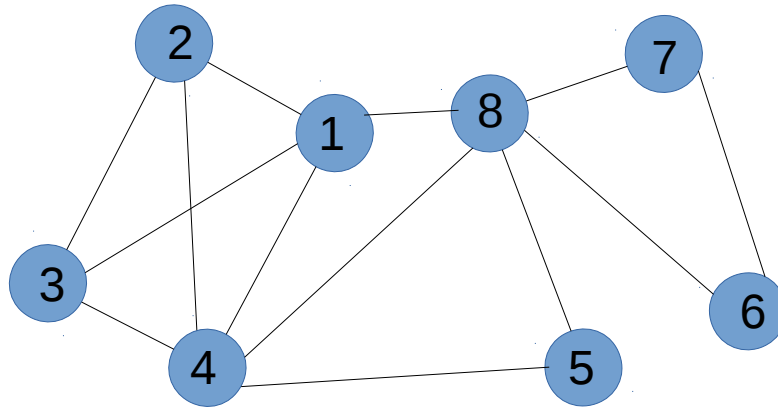


$$\lambda_1 = 0$$

$$\lambda_2 = 0.764$$

$$L = \begin{bmatrix} 4 & -1 & -1 & -1 & 0 & 0 & 0 & -1 \\ -1 & 3 & -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & -1 & 4 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 4 & -1 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & 3 & -1 & -1 \\ 0 & 0 & 0 & 0 & -1 & -1 & 3 & -1 \\ -1 & 0 & 0 & 0 & -1 & -1 & -1 & 4 \end{bmatrix} \quad v_2 = \begin{bmatrix} 0.263 \\ 0.425 \\ 0.425 \\ 0.263 \\ -0.263 \\ -0.425 \\ -0.425 \\ -0.263 \end{bmatrix}$$

# Example Graph 3

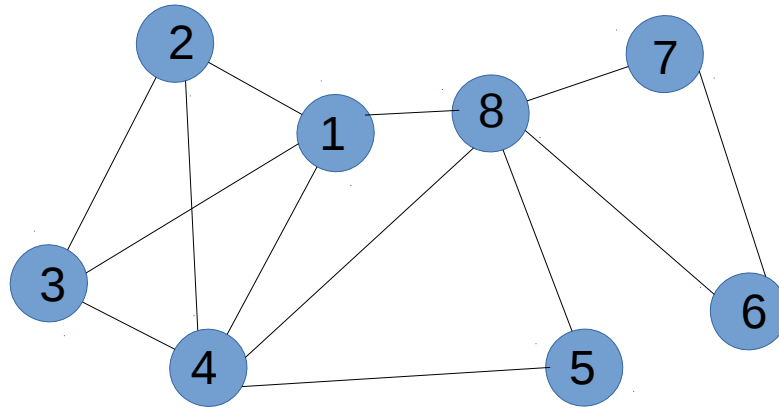


$$\lambda_1 = 0$$

$$\lambda_2 = 0.748$$

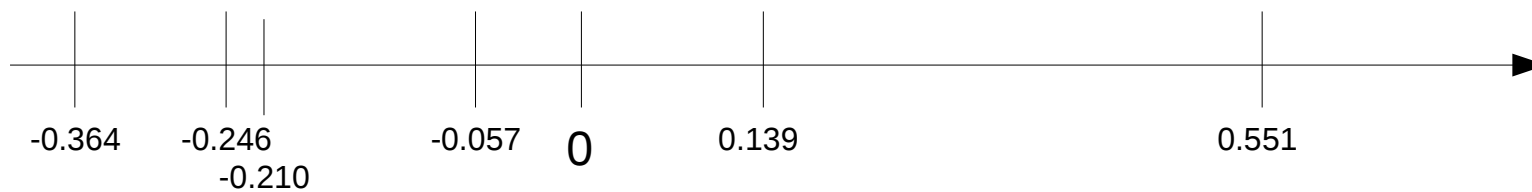
$$L = \begin{bmatrix} 4 & -1 & -1 & -1 & 0 & 0 & 0 & -1 \\ -1 & 3 & -1 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & 3 & -1 & 0 & 0 & 0 & 0 \\ -1 & -1 & -1 & 5 & -1 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 & 2 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 2 & -1 & -1 \\ 0 & 0 & 0 & 0 & 0 & -1 & 2 & -1 \\ -1 & 0 & 0 & -1 & -1 & -1 & -1 & 5 \end{bmatrix} \quad v_2 = \begin{bmatrix} -0.246 \\ -0.364 \\ -0.364 \\ -0.210 \\ -0.057 \\ 0.551 \\ 0.551 \\ 0.139 \end{bmatrix}$$

# Example Graph 3, projected



$$\lambda_1 = 0$$

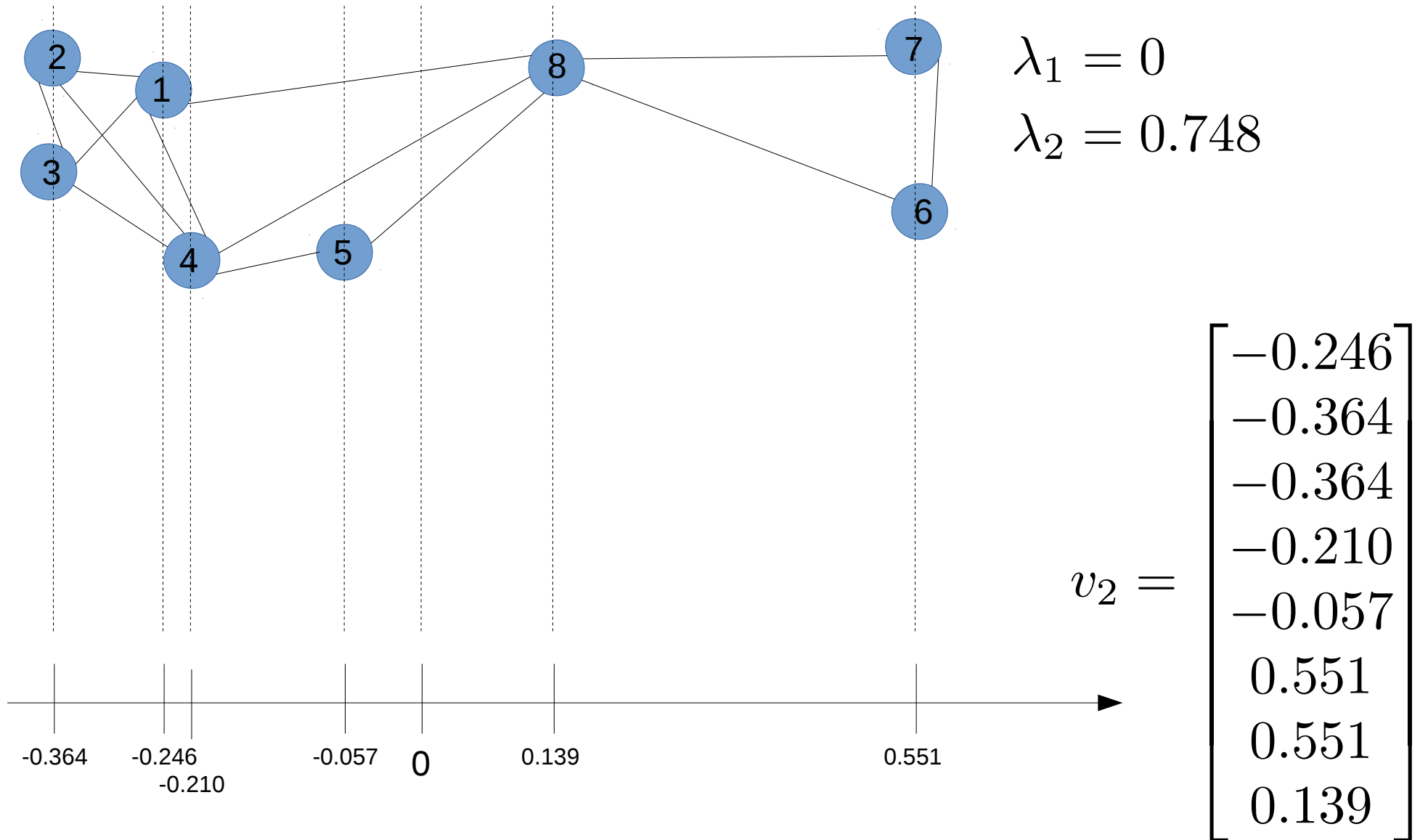
$$\lambda_2 = 0.748$$



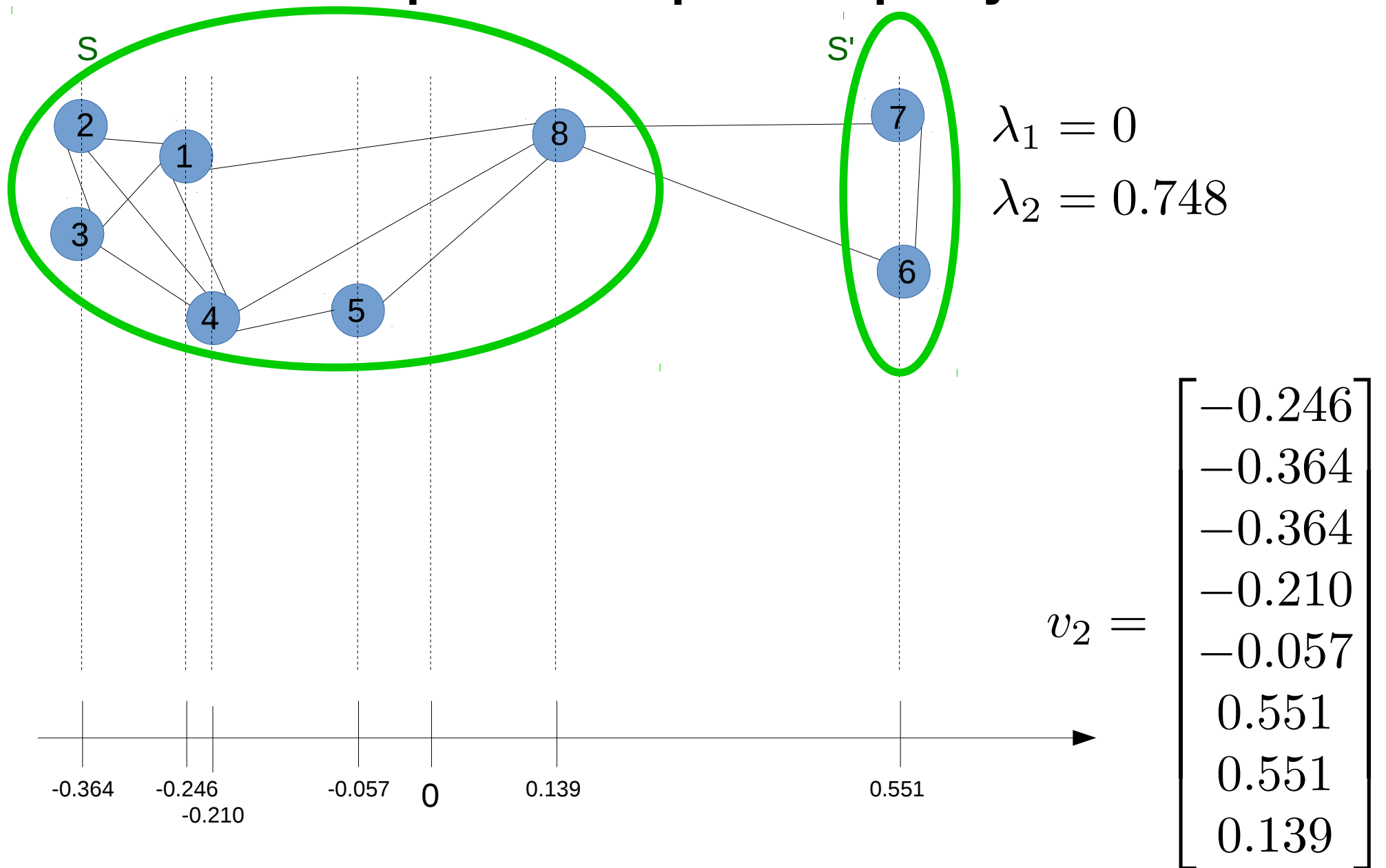
$v_2 =$

$$\begin{bmatrix} -0.246 \\ -0.364 \\ -0.364 \\ -0.210 \\ -0.057 \\ 0.551 \\ 0.551 \\ 0.139 \end{bmatrix}$$

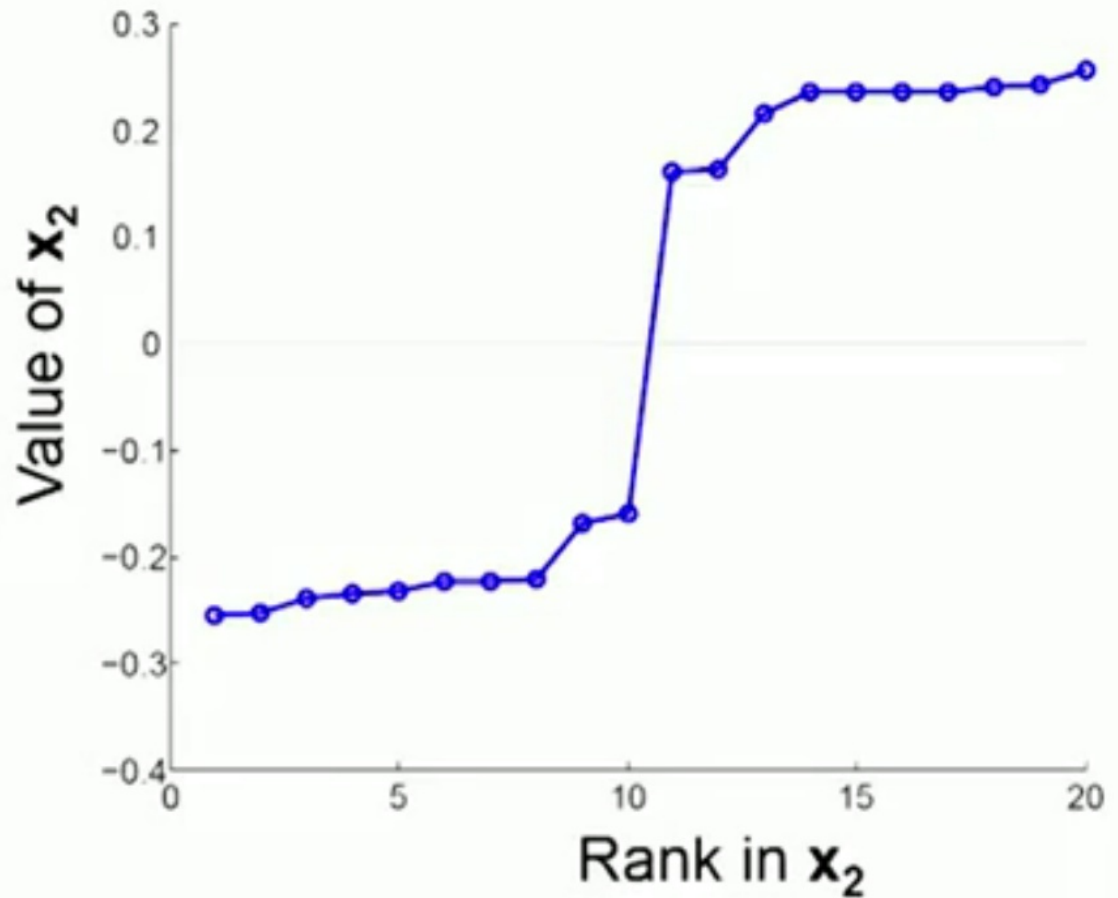
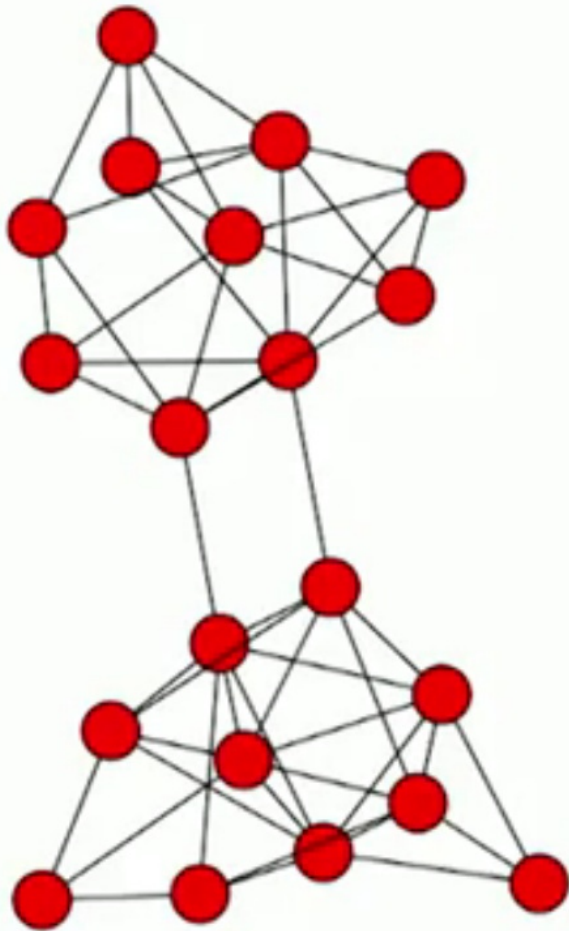
# Example Graph 3, projected *how to partition?*



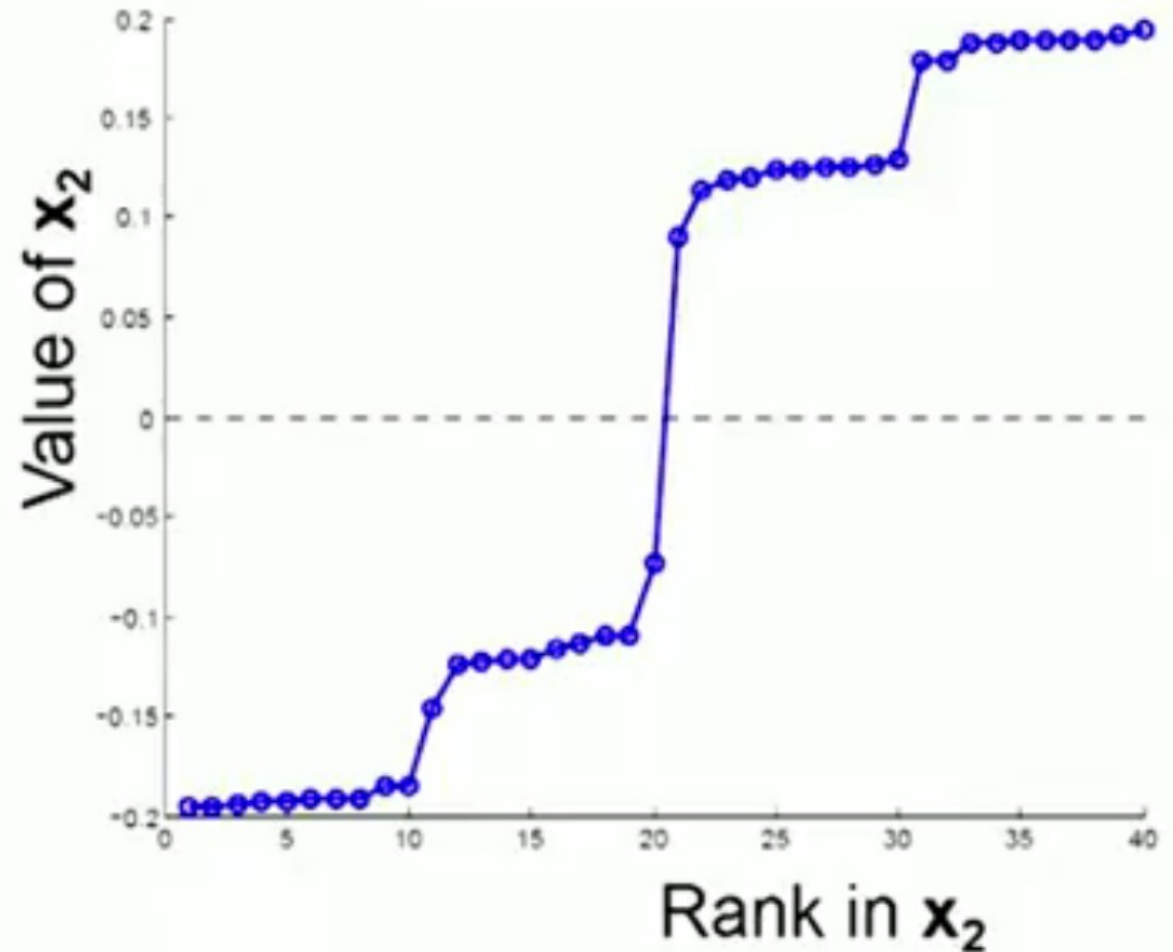
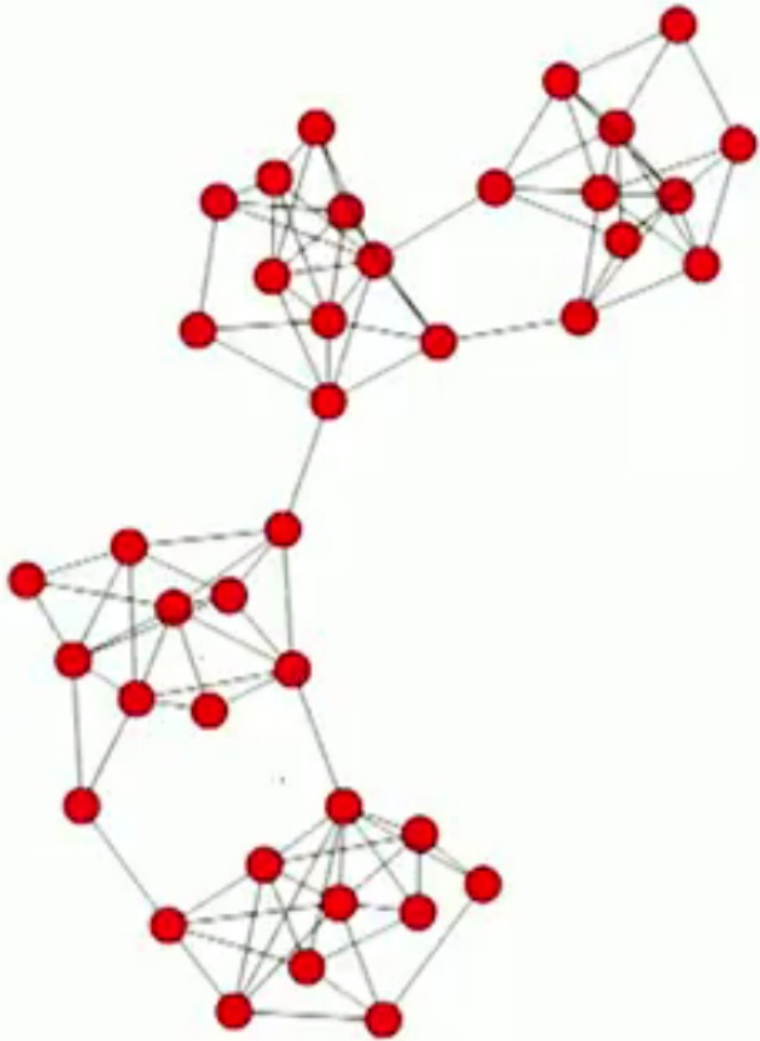
# Example Graph 3, projected



# A more complex graph

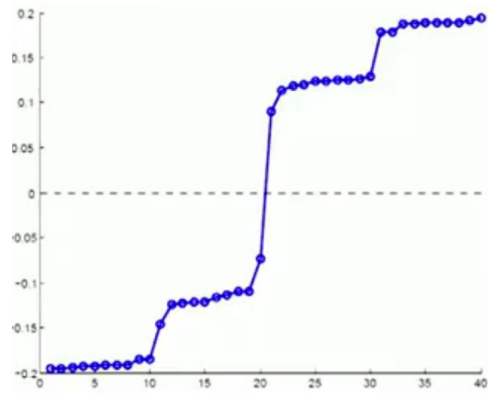
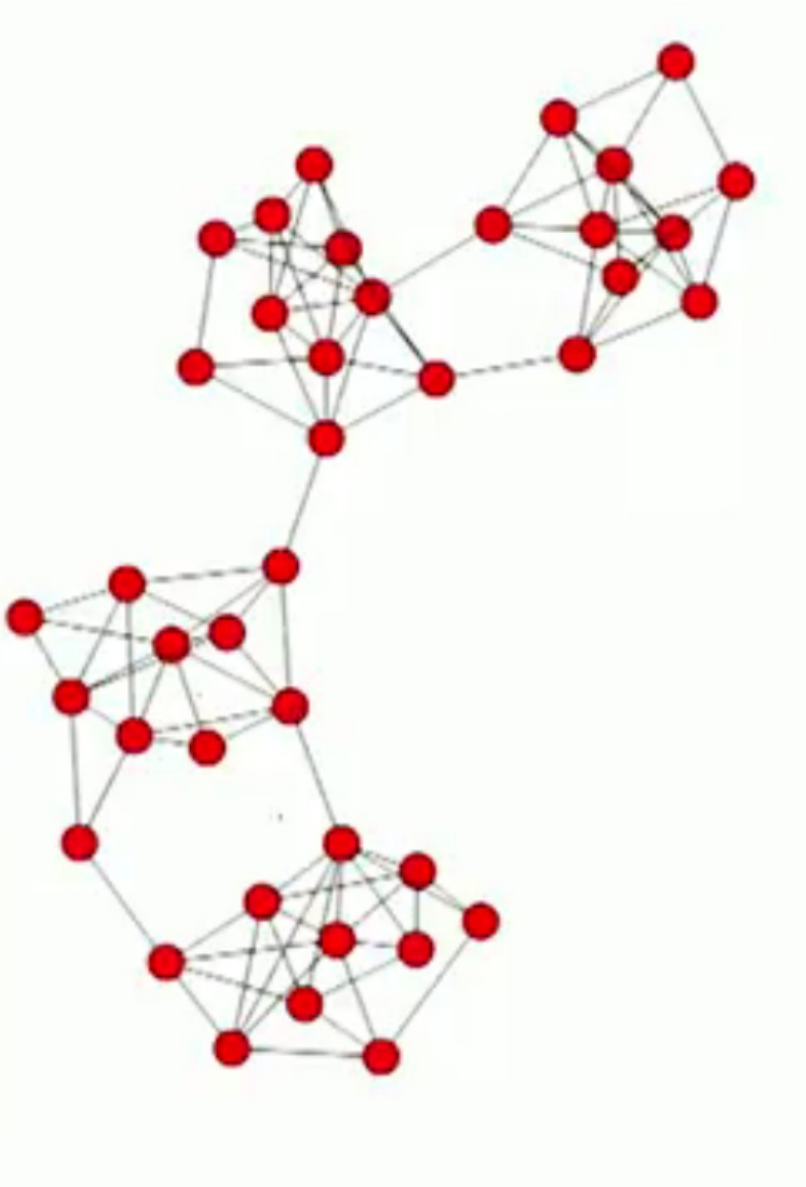


# A graph with 4 “communities”

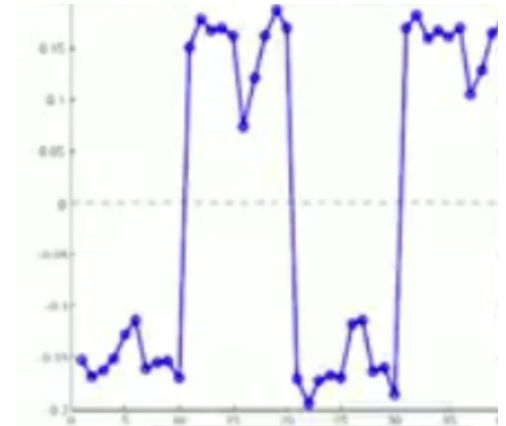




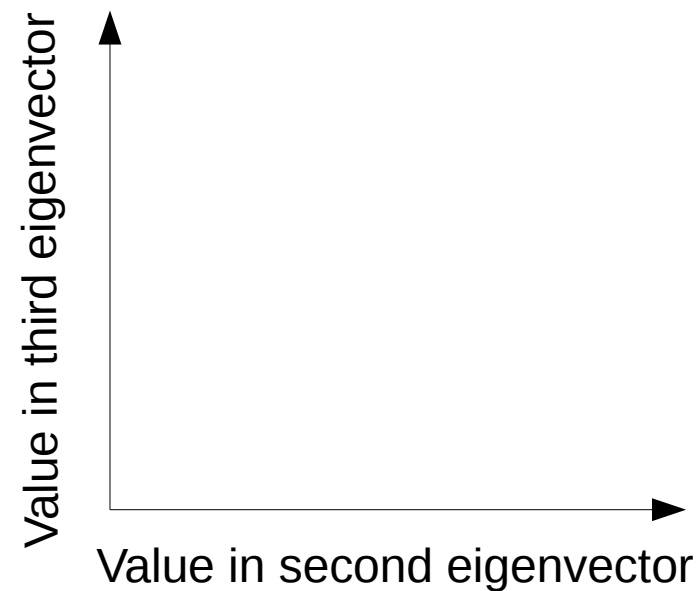
# Other eigenvectors



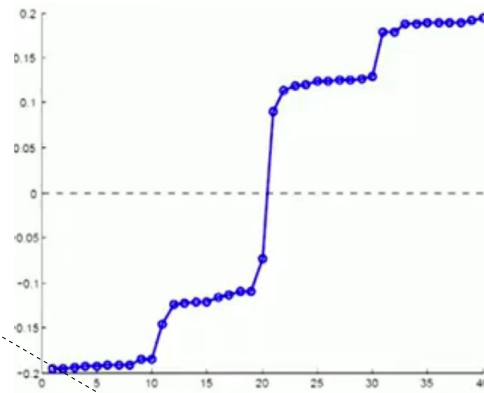
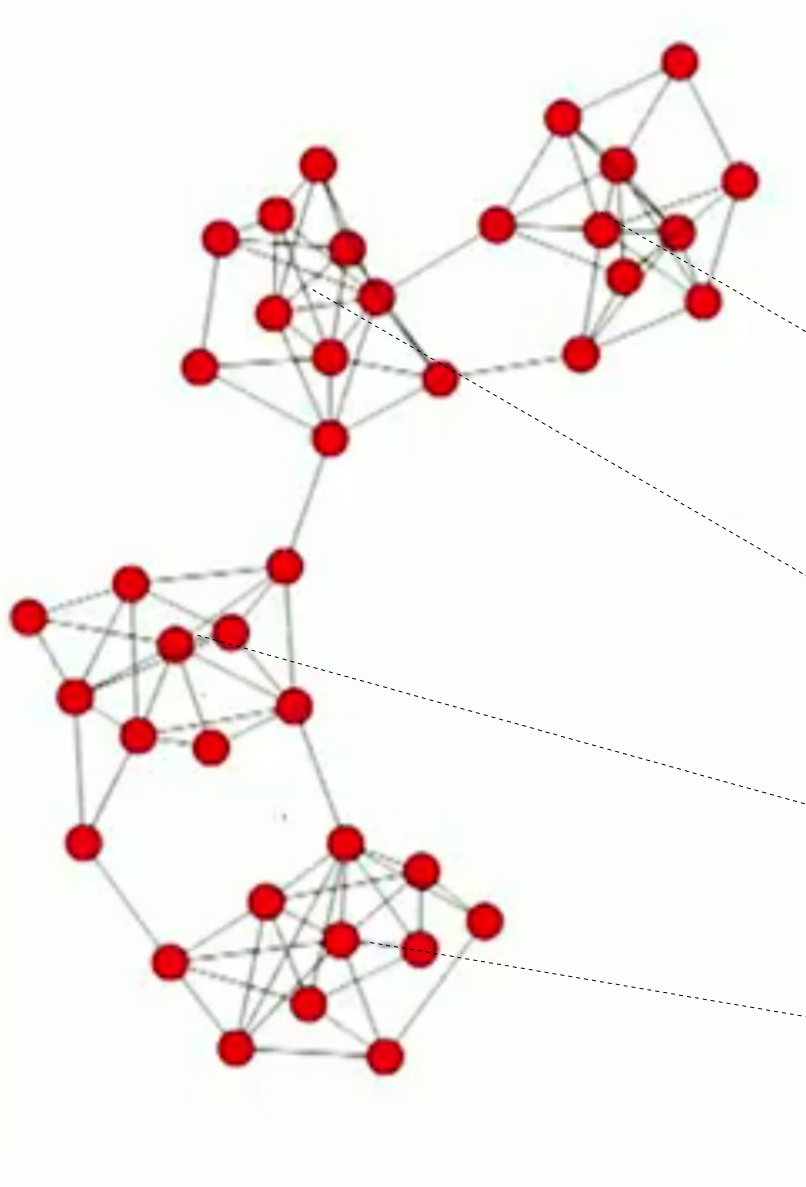
Second eigenvector



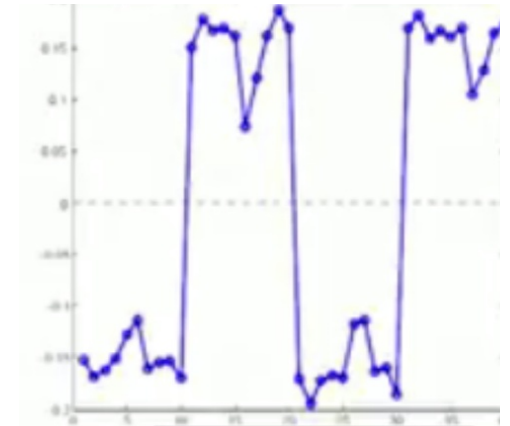
Third eigenvector



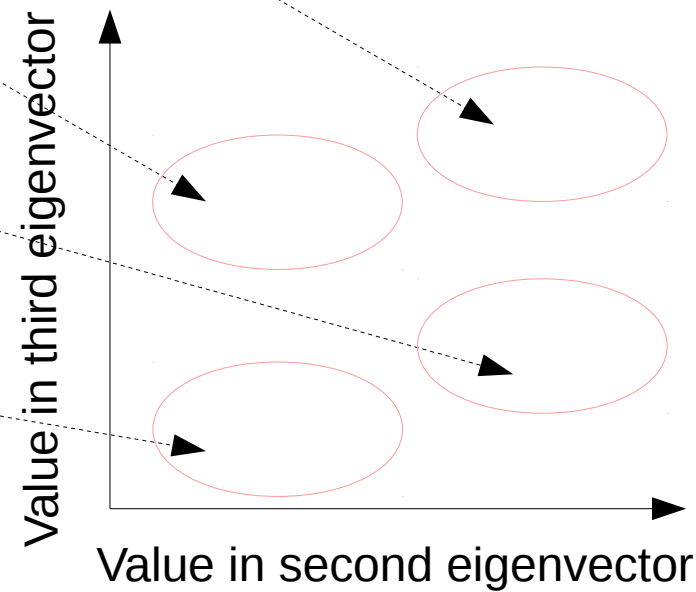
# Other eigenvectors



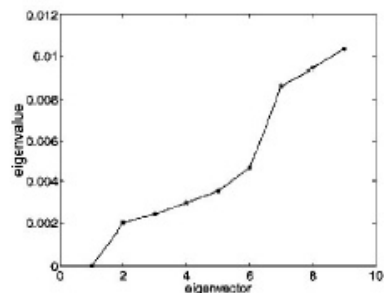
Second eigenvector



Third eigenvector



# Interesting application: image segmentation [Shi & Malik 2000]



(a)

(b)

(c)

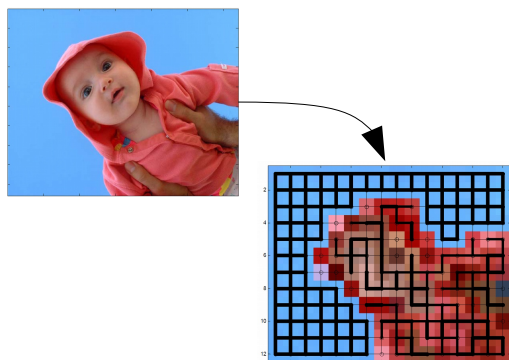
Transform into grid graph with edge weights proportional to pixel similarity



(d)

(e)

(f)



(g)

(h)

(i)

# Lots of examples, including one of embedding streets in Rome

