Spectral Graph Theory

Why are graphs required?

It is a mathematical structures used to model pairwise didactic relationship between objects.

Examples of Graphs

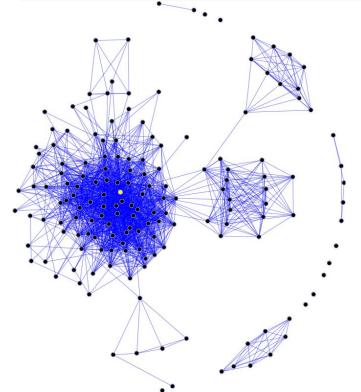
Social Networks

Road Networks

Robotics

Communication networks

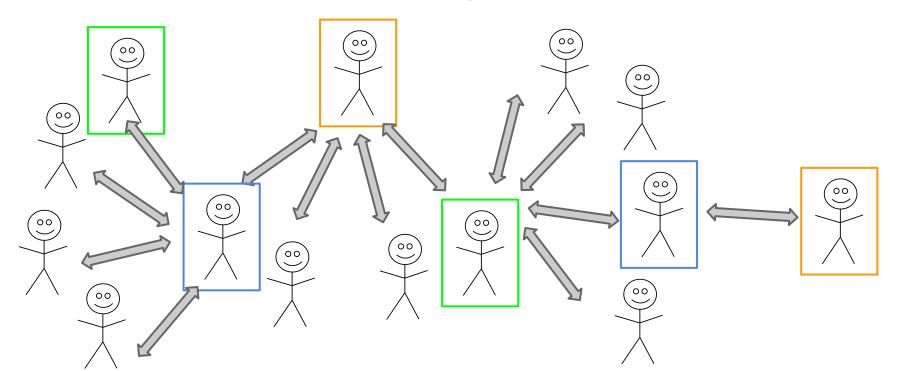
A drawing of a graph in which each person is represented by a dot called node and the friendship relationship is represented by a line called edge



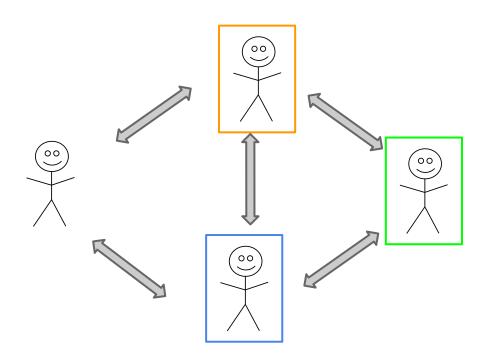




Friends have to be re-represented in trees.



Friends represented only once in graphs



Nodes can be:

Best Friends

Colleagues

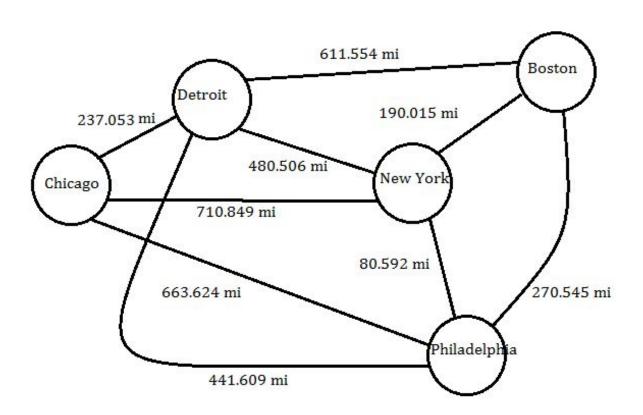
Home town

Edges can be:

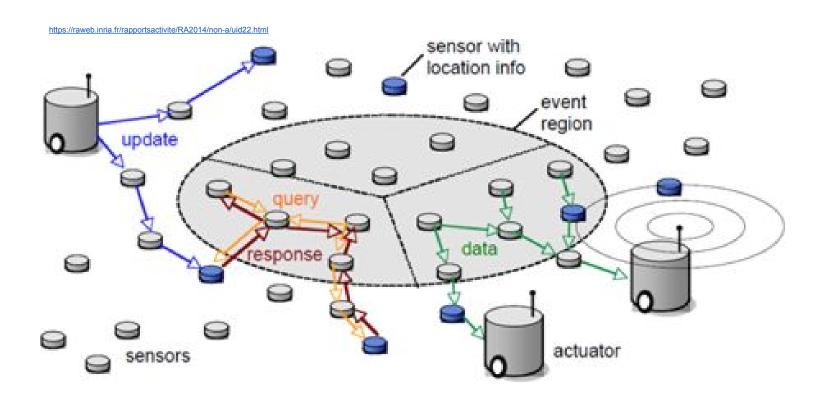
Friendship

Weighted edges can be interactions between friends.

Road Networks



Robotics



Representing a Graph

VARIOUS MATRIX REPRESENTATIONS OF A GRAPH

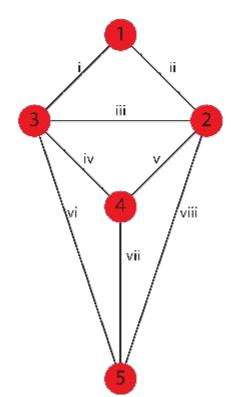
Adjacency Matrix

- Adjacency Matrix represents which <u>vertices</u> (or nodes) of a graph are connected to one another.
- Consider a Graph $G = \{V,E\}$. And G has n number of vertices, then the Adjacency Matrix (A) is a $n \times n$ Matrix.
- An element \underline{a}_{ij} in the matrix A, is 1 when the vertices v_i and \underline{v}_j are connected. For undirected graphs, \underline{a}_{ij} is the same value as \underline{a}_{ij} .
- For weighted Graphs, \underline{a}_{ij} is equal to the weight of the edge between v_i and \underline{v}_i . It is also usually referred to as \underline{w}_{ij} .

Adjacency Matrix (Contd...)

The graph is undirected, and each edge weight of the graph is 1.

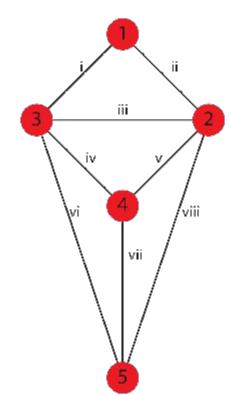
n = 5; m = 8.



Adjacency Matrix (Contd...)

The graph is undirected, and each edge weight of the graph is 1.

n = 5; m = 8.



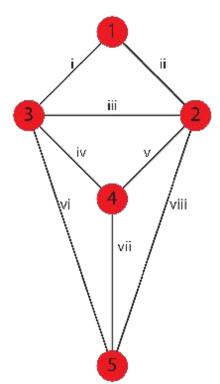
Degree Matrix

It is a diagonal n x n matrix.

Each value <u>dii</u> denotes the degree of the vi.

Degree Matrix (Contd...)

2	0	0	0	0
0	4	0	0	0
0	0	4	0	0
0	0	0	3	0
0	0	0	0	3



Incidence Matrix

In general, it is a matrix showing the relationship between two classes of objects.

The first class is X and the second class is Y, the matrix has one row for each element of X and one column for each element of Y.

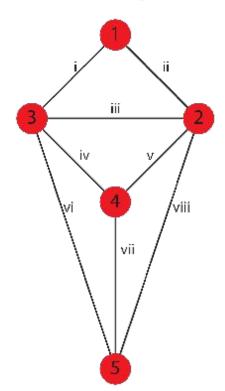
For a graph, the first class is the <u>vertices</u> and the second class is the edges. An xm matrix.

For an undirected graph, for a given edge (<u>I.e.</u> for a column), two row values are 1, rest are 0.

For a directed graph, the vertex of the origin of edge is -1, and the destination vertex of the edge is 1.

Incidence Matrix (Contd...)

1	1	0	0	0	0	0	0
0	1	1	0	1	0	0	1
1	0	1	1	0	1	0	0
0	0	0	1	1	0	1	0
0	0	0	0	0	1	1	1



Graph Information

d dimensional.

Can be compared to a manifold.

No standard basis vector. (X and Y vectors in images).

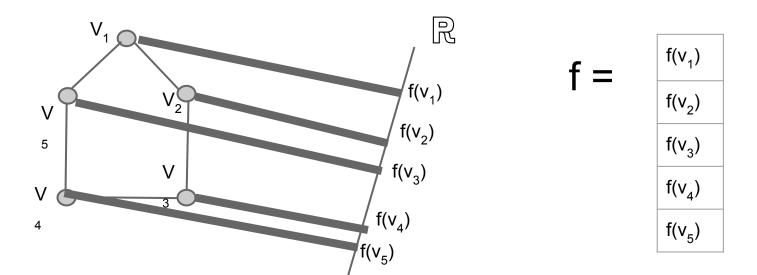
Relation to Manifold

Consider local area

Consider euclidean distance between these distances

Function on a graph

A function on a graph maps the vertices of the graph to real numbers. $f: V \rightarrow \mathbb{R}$



What is Laplacian?

A differential operator given by the divergence of a function in euclidean space.

Laplacian in Images

0	-1	0
-1	4	-1
0	-1	0

$$\Delta f = (\partial^2 f / \partial x^2) + (\partial^2 f / \partial y^2)$$

$$\Delta f = \nabla^2 f = (\nabla . \nabla) f = \nabla^T \nabla f$$

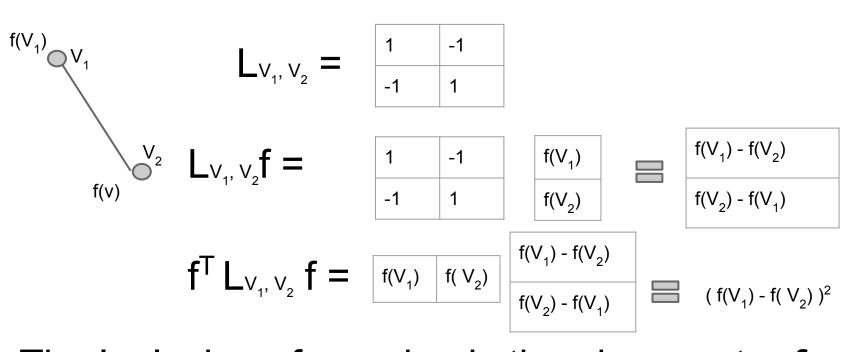
Laplacian of n dimensions

2 Dimensions: $\Delta f = (\partial^2 f / \partial x^2) + (\partial^2 f / \partial y^2)$

3 Dimensions: $\Delta f = (\partial^2 f / \partial x^2) + (\partial^2 f / \partial y^2) + (\partial^2 f / \partial z^2)$

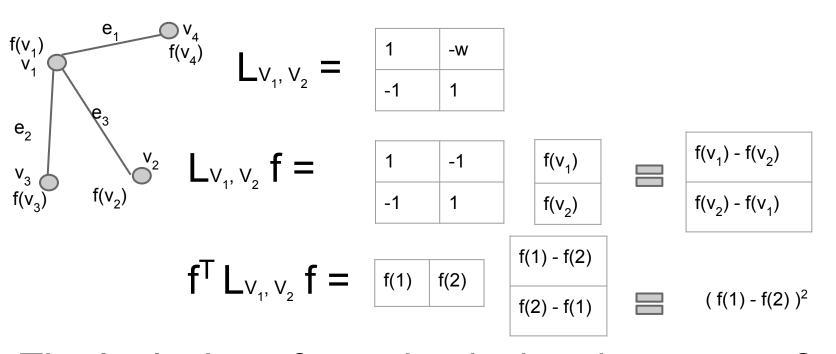
n Dimensions:
$$\Delta f = (\partial^2 f / \partial^2 x_1) + (\partial^2 f / \partial^2 x_2) + \dots + (\partial^2 f / \partial^2 x_n)$$

Finding Laplacian for an edge



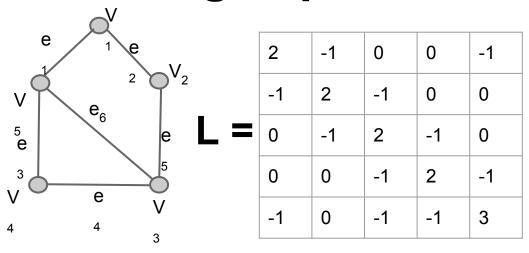
The laplacian of an edge is the eigenvector \mathbf{f} , s.t, $L_{V_1, V_2} \mathbf{f} = (\mathbf{f}(V_1) - \mathbf{f}(V_2))^2$

Finding Laplacian for an edge



The laplacian of an edge is the eigenvector \mathbf{f} , s.t, L_{11} , $f = (f(1) - f(2))^2$

Finding Laplacian of Graphs





	V ₁	V ₁	V ₃	V ₄	V ₅
e ₁	1	0	0	0	-1
e ₂	1	-1	0	0	0
e ₃	0	0	0	1	-1
e ₄	0	0	1	-1	0
e ₅	0	1	-1	0	0
e ₆	0	0	1	0	-1

$$f L f = f \nabla^T \nabla f$$

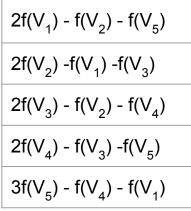
1	1	0	0	0	0
0	-1	0	0	1	0
0	0	0	1	-1	1
0	0	1	-1	0	0
-1	0	-1	0	0	-1

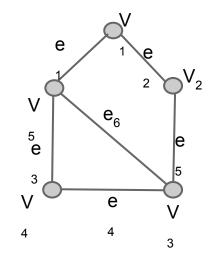
L		7	7	∇	
	0	0	1_	0	-1
-1	0	1	-1	0	0
0	0	0	1	-1	0
1	0	0	0	1	-1
0	1	-1	0	0	0
0	1	0	0	0	-1

 $f L f = f \nabla^T \nabla$

2	-1	0	0	-1
-1	2	-1	0	0
0	-1	2	-1	0
0	0	-1	2	-1
-1	0	-1	-1	3

$$\nabla^{\mathsf{T}} \nabla \mathbf{f} = \begin{bmatrix}
2 & -1 & 0 & 0 & -1 & f(V_1) \\
-1 & 2 & -1 & 0 & 0 & f(V_2) \\
0 & -1 & 2 & -1 & 0 & f(V_3) & f(V_4) \\
0 & 0 & -1 & 2 & -1 & 3 & f(V_5)
\end{bmatrix}$$





$$f \nabla^T \nabla f =$$

$$[2f(V_1) - f(V_2) - f(V_5)]^2$$

$$[2f(V_2) - f(V_1) - f(V_3)]^2$$

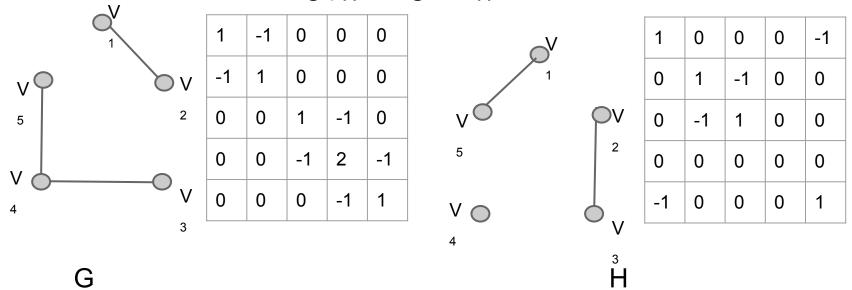
$$[2f(V_3) - f(V_2) - f(V_4)]^2$$

$$[2f(V_4) - f(V_3) - f(V_5)]^2$$

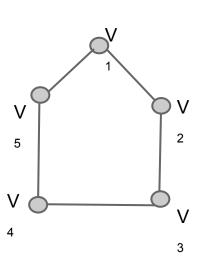
$$[3f(V_5) - f(V_4) - f(V_1)]^2$$

Edge Union - If G and H are 2 graphs on the same vertex set with disjoint edge sets,

$$L_{G \cup H} = L_G + L_H$$
(Additivity)



Edge Union - If G and H are 2 graphs on the same vertex set with disjoint edge sets,



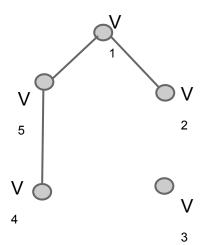
 $L_{GUH} = L_{G} + L_{H}$ (Additivity)

1	-1	0	0	0
-1	1	0	0	0
0	0	1	-1	0
0	0	-1	2	-1
0	0	0	-1	1

0	0	0	-1
1	-1	0	0
-1	1	0	0
0	0	0	0
0	0	0	1
	1 -1 0	1 -1 -1 1 0 0	1 -1 0 -1 1 0 0 0 0

2	-1	0	0	-1
-1	2	-1	0	0
0	-1	2	-1	0
0	0	-1	2	-1
-1	0	0	-1	2

Disjoint Union - If a vertex i∈G is isolated, then the corresponding row and column of the laplacian are 0.



2	-1	0	0	-1
-1	2	0	0	0
0	0	0	0	0
0	0	0	2	-1
-1	0	0	-1	2

Isolated Vertex - The properties of Isolated Vertices and Disjoint Union together implies that the disjoint union of G and H is the sum of L_G and L_H

$$L_{G \cup H} = L_{G} + L_{H} = \begin{bmatrix} L_{G} & 0 \\ 0 & L_{H} \end{bmatrix}$$

Disjoint Union Spectrum - If L_G has eigenvectors v_1, v_2, \ldots, v_n with eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_n$ and L_H has eigenvectors w_1, w_2, \ldots, w_n with eigenvalues $\mu_1, \mu_2, \ldots, \mu_n$ then $L_{G \cup H}$ has eigenvectors

 v_1 + **0**,, v_n + **0**, **0** + w_1 ,, **0** + w_n and the corresponding eigenvalues

$$\lambda_1, \lambda_2, \dots, \lambda_n, \mu_1, \mu_2, \dots, \mu_n$$

Fundamental Theorem of Spectral Graph Theory

 $L = I - D^{-1/2}AD^{-1/2}$

L is symmetric, all its eigenvalues are real.

A = Adjacency matrix

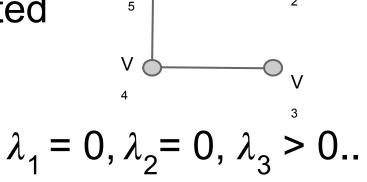
D the diagonal martix of degree of each vertex.

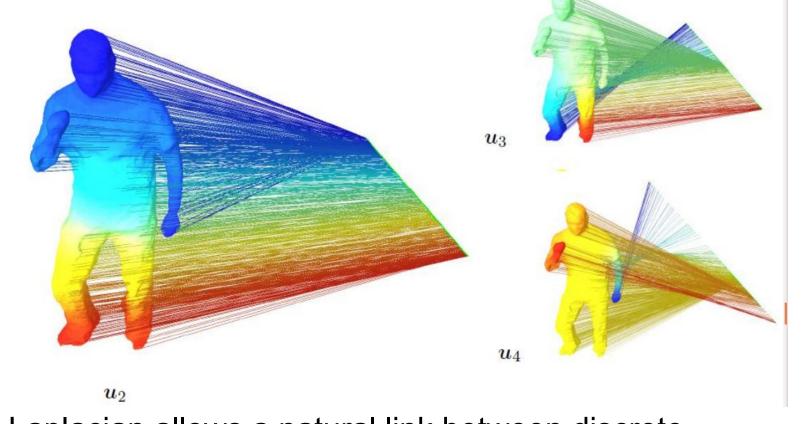
Fundamental Theorem of Spectral Graph Theory

Let $0 = \lambda_1 <= \lambda_2 <= \dots \lambda_n$ be the eigenvalues of L in sorted order with multiplicities. Then,

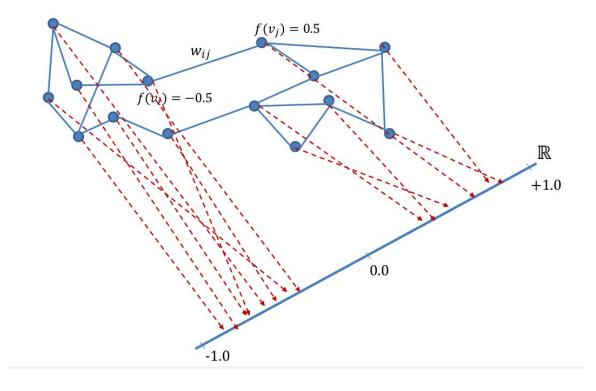
$$\lambda_1 = 0$$
 and $\lambda_n <= 2$
 $\lambda_k = 0$ iff G has >= k connected
components

 λ_n = 2 iff G has a bipartitite connected component.





The Laplacian allows a natural link between discrete representations (graphs), and continuous representations, such as metric spaces and manifolds.



Laplacian embedding consists in representing the vertices of a graph in the space spanned by the smallest eigenvectors of the Laplacian.

The Fiedler vector of the Laplacian

The first non-null eigenvalue λ_{k+1} is called the Fiedler value. The corresponding eigenvector u_{k+1} is called the Fiedler vector.

The multiplicity of the Fiedler eigenvalue depends on the graph's structure and it is difficult to analyse.

The Fiedler value is the algebraic connectivity of a graph, the further from 0, the more connected.