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Unit - 4 ↗ Spectral Graph Theory

Introduction

- This unit focused on
- **Key Question:** How can we analyze the structure of a graph using matrices and the spectrum of associated operators?
- We learned about the **Adjacency Matrix**, **Degree Matrix**, and the **Laplacian Matrix**, which encode structural information about graphs in algebraic form.
- We explored the **Cut-Set Matrix** to understand graph partitions and connectivity patterns.
- We also studied **Eigenvalues and Eigenvectors** of these matrices to reveal deep properties of graphs, such as connectivity, expansion, and clustering.
- These tools are powerful in real-world applications like ranking in networks, image segmentation, and machine learning on graphs.

Method – 1 ↳ Matrix Representation of graphs

Definition: Let $G = (V, E)$ be a graph with n vertices and without parallel edges. The adjacency matrix of graph $G = (V, E)$ is denoted as A or $A(G)$ and is defined as $n \times n$ matrix $A = [a_{ij}]$ whose elements a_{ij} are given as follows:

$$a_{ij} = \begin{cases} 1, & \text{if } v_i \text{ is adjacent to } v_j \\ 0, & \text{otherwise} \end{cases}$$

Definition: Let $G = (V, E)$ be a graph with n vertices. The degree matrix of graph $G = (V, E)$ is denoted as D or $D(G)$ and is defined as $n \times n$ diagonal matrix $D = [d_{ij}]$ whose elements d_{ij} are given as follows:

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

Where, $d(v_i)$ is the degree of vertex v_i .

Definition: Let $G = (V, E)$ be a simple graph with n vertices. The Laplacian matrix of graph $G = (V, E)$ is denoted as $L(G)$ and is defined as $n \times n$ matrix $L = [l_{ij}]$ whose elements l_{ij} are given as follows:

$$d_{ij} = \begin{cases} -1, & \text{if } v_i \text{ is adjacent to } v_j \\ d(v_i), & \text{if } i = j \\ 0, & \text{otherwise} \end{cases}$$

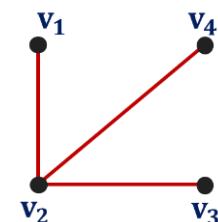
Where, $d(v_i)$ is the degree of vertex v_i .

→ Equivalently $L = D - A$, where D is the degree matrix, and A is the graph's adjacency matrix.

Example: Find Laplacian matrix of the following graph.

Solution: Here first we find adjacency matrix of the given graph.

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



Now we find Degree matrix of the given graph.

$$D = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

$$\text{Hence, Laplacian matrix } L = D - A = \begin{bmatrix} 1 & -1 & 0 & 0 \\ -1 & 3 & -1 & -1 \\ 0 & -1 & 1 & 0 \\ 0 & -1 & 0 & 1 \end{bmatrix}.$$

Example of Method-1: Matrix Representation of Graph

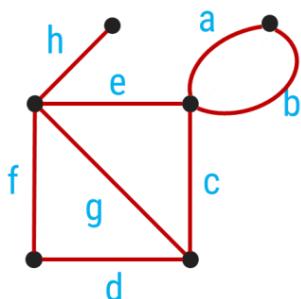
C	1	Find an adjacency matrix for the following graph.
C	2	Find the degree matrix for the following graph.
C	3	Find the Laplacian matrix for the following graph.
C	4	Find the Laplacian matrix for the following graph.
C	5	Find the Laplacian matrix for the following graph.
H	6	Find the Laplacian matrix of K_5 .
H	7	Find the Laplacian matrix of C_5 .
H	8	Find the Laplacian matrix of $K_{4,4}$.

Method – 2 ↗ Cut-set Matrix and it's properties

Definition: Let $G = (V, E)$ be a graph. The cut-set matrix of graph $G = (V, E)$ is denoted as C or $C(G)$, in which the rows correspond to the cut-sets and the columns to the edges of the graph and is defined as matrix $C = [c_{ij}]$ whose elements c_{ij} are given as follows:

$$c_{ij} = \begin{cases} 1, & \text{if } i^{\text{th}} \text{ cutset contains } j^{\text{th}} \text{ edge} \\ 0, & \text{otherwise} \end{cases}$$

Example: Find Cut-Set Matrix for Following Graph

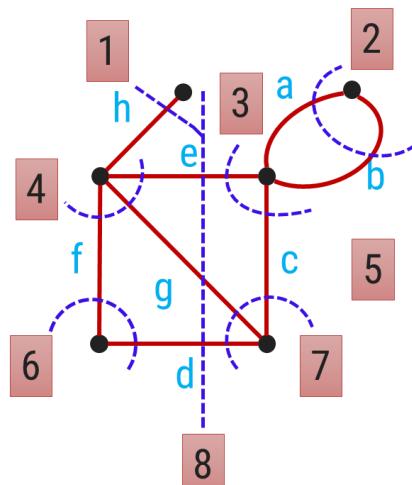


Solution: Here, given graph have 8 cut set and 8 edges.

That means we get 8×8 cut-set matrix of given graph.

$$C = [c_{ij}]_{8 \times 8} =$$

	a	b	c	d	e	f	g	h
1	0	0	0	0	0	0	0	1
2	1	1	0	0	0	0	0	0
3	0	0	1	0	1	0	0	0
4	0	0	0	0	1	1	1	0
5	0	0	1	0	0	1	1	0
6	0	0	0	1	0	1	0	0
7	0	0	1	1	0	0	1	0
8	0	0	0	1	1	0	1	0



Definition: Let $G = (V, E)$ be a graph with n vertices and e edges. The fundamental cut-set matrix of graph G is $n - 1 \times e$ denoted as C_f , which sub matrix of C such that the rows correspond to the set of fundamental cut-sets with respect to some spanning tree.

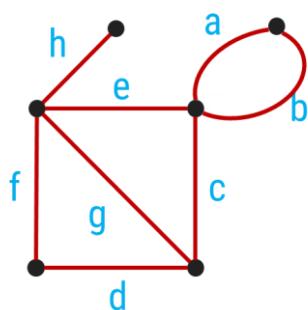
A fundamental cut-set matrix C_f can also be partitioned into two sub matrices, one of which is an identity matrix I_{n-1} , of order $n - 1$. That is

$$C_f = [C_c | I_{n-1}]$$

Properties:

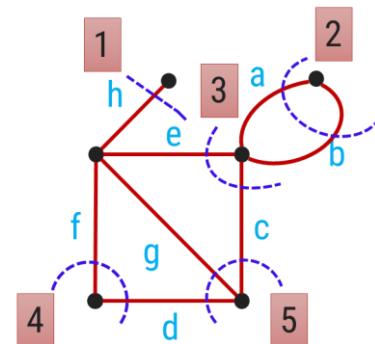
1. The last $n - 1$ columns of fundamental cutset matrix forming the identity matrix correspond to the $n - 1$ branches of the spanning tree.
2. The first $e - n + 1$ columns forming C_c correspond to the chords.
3. Rank of cut-set matrix = Rank of the fundamental cutset matrix = Rank of graph.

Example: Find Fundamental Cut-Set Matrix for the Following Graph



Solution:

- First we consider any spanning tree of given graph.
- Say $\{h, e, f, g, a\}$.
- Now, we find all of its fundamental cut sets.
- Here, graph have 5 fundamental cut set and 8 edges. As graph have 5 branches and 3 chord.
- That means we get 5×8 fundamental cut-set matrix of given graph.
- Hence, in fundamental cutset matrix the last 5 columns forming the identity matrix correspond to the 5 branches of the spanning tree, and the first 3 columns forming C_c correspond to the chords.



$$C = [c_{ij}]_{5 \times 8} = [C_c | I_5]$$

Chords			Branches					
	b	c	d	a	e	f	g	h
1	1	0	0	1	0	0	0	0
2	0	1	0	0	1	0	0	0
3	0	0	1	0	0	1	0	0
4	0	1	1	0	0	0	1	0
5	0	0	0	0	0	0	0	1

Some Application of Fundamental Cutset Matrix:

Problem:

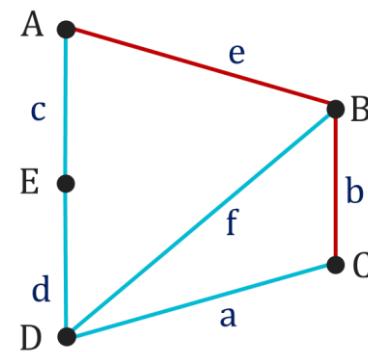
A company has 5 servers connected as follows: (A-B), (B-C), (C-D), (D-E), (A-E), (B-D)

Tasks:

- Compute the rank of the graph.
- Construct a fundamental cut-set matrix using a spanning tree.
- Identify the minimum link failures that disconnect the network.

Solution:

- First we draw graph from given instruction.
- We have given that: A company has 5 servers connected as follows:
 $(A - B), (B - C), (C - D), (D - E), (A - E), (B - D)$
- Consider spanning tree of following graph (blue lines).
- Now, we find all of its fundamental cut sets corresponding to all of its branch.
- Here, graph have 4 fundamental cut set and 6 edges. As graph have 4 branches and 2 chord.
- That means we get 4×6 fundamental cut-set matrix of given graph.
- Hence, in fundamental cutset matrix the last 4 columns forming the identity matrix correspond to the 4 branches of the spanning tree, and the first 2 columns forming C_c correspond to the chords.



	b	e	c	a	f	d
1	0	1	1	0	0	0
2	1	0	0	1	0	0
3	1	1	0	0	1	0
4	0	1	0	0	0	1

- So, in fundamental cut set matrix we have row with two 1's which is the minimum that means 2 edges (for e.g. e, c) is the minimum link failures that disconnect the network.
- Also from fundamental cutset matrix it is clear that rank of graph is 4.

Example of Method-2: Cut-set Matrix and it's properties

C	1	Find the cut-set matrix for the following graph.	
C	2	Find Fundamental Cut-Set Matrix For Following Graph	
C	3	Find the Fundamental Cut-Set Matrix For Following Graph with respect to given spanning tree (green lines).	
C	4	A network of 6 servers has edges: (A-B), (B-C), (C-D), (D-E), (E-F), (A-F), (B-E). Tasks: <ol style="list-style-type: none">1. Compute rank.2. Construct a fundamental cut-set matrix using a spanning tree.3. Identify the minimum link failures that disconnect the network.	
H	5	Find the fundamental cutset matrix for K_5 .	
H	6	Find the fundamental cutset matrix of S_5 .	
H	7	Find the fundamental cutset matrix of C_5 .	
H	8	Find the fundamental cutset matrix of the following graph.	

Method - 3 ↳ Eigen Values and Eigen Vector

Eigen Values and Eigen Vectors

- Let A be an $n \times n$ matrix, then the scalar λ is known as **eigen value** of A, if there exists a non-zero vector X such that $AX = \lambda X$.
- The **non-zero** vector X is known as **eigen vector** of A corresponding to eigen value λ .

Characteristic Equation

- Let A be a square matrix of order n and I be an identity matrix of order n. Then $|A - \lambda I| = 0$ is known as characteristic equation, where λ is a scalar.
- The characteristic equation of matrix A of order 2×2 is $\lambda^2 - S_1\lambda + S_2 = 0$ where $S_1 = \text{tr}(A)$ and $S_2 = |A|$
- The characteristic equation of matrix A of order 3×3 is $\lambda^3 - S_1\lambda^2 + S_2\lambda - S_3 = 0$ where $S_1 = \text{tr}(A)$, $S_2 = \text{sum of minors of principal diagonal elements}$ and $S_3 = |A|$

Remarks

- Let A be a square matrix of order n, then
 - A n eigen value of A is a scalar λ such that $|A - \lambda I| = 0$.
 - The eigen vectors of A corresponding to eigen value λ are the non-zero solutions of the system $(A - \lambda I) \cdot X = 0$.
- Eigen value is also known as characteristic root/latent value/proper roots and eigen vector is known as characteristic vector/latent vector/proper vector corresponding to the eigen value λ of the matrix.
- The set of all eigenvalues of matrix A is called Spectrum of A.

Properties of Eigen Value and Eigen Vector

- $\text{Trace}(A) = \text{Sum of all the eigen values of matrix } A$
- $\text{Det}(A) = \text{Product of all the eigen values of matrix } A$
- If one of the eigen value of matrix A is zero, then $|A| = 0$, hence A^{-1} does not exist.
- The eigen values of triangular matrix are the elements on its principal diagonal.
- The square matrix A and A^T have the same eigen values but eigen vectors need not to be same.
- If λ is an eigen value of a non-singular matrix A and X is an eigen vector corresponding to λ , then
 - Eigen value of A^{-1} is $\frac{1}{\lambda}$ and X is corresponding eigen vector.

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- Eigen value of A^k is λ^k and X is corresponding eigen vector; $k \in \mathbb{R}$
- Eigen value of $A \pm kI$ is $\lambda \pm k$; $k \in \mathbb{R}$
- Eigen value of kA is $k\lambda$; $k \in \mathbb{R}$

→ **Procedure to find the eigen values, eigen vectors for a matrix A of order 3×3**

- Write the characteristic equation $\lambda^3 - S_1\lambda^2 + S_2\lambda - S_3 = 0$ and find S_1, S_2 and S_3 .
- Find the roots of the characteristic equation. These are the Eigen Values of A, say $\lambda_1, \lambda_2, \lambda_3$.
- Solve the homogeneous system $(A - \lambda I) \cdot X = 0$ for each eigen value by using Gauss Elimination Method.
- Eigen vector is the solution X of above system.

→ The procedure remains same for the matrices of order 2.

Remarks:

A matrix is invertible if its inverse exists.

Example of Method-3: Eigen Values and Eigen Vector

C	1	<p>Find the eigen values and eigen vectors of the matrix $A = \begin{bmatrix} 3 & 1 & 4 \\ 0 & 2 & 6 \\ 0 & 0 & 5 \end{bmatrix}$.</p> <p>Answer: $\lambda = 2 \rightsquigarrow X = [-1 \ 1 \ 0]^T, \quad \lambda = 3 \rightsquigarrow X = [1 \ 0 \ 0]^T$ $\lambda = 5 \rightsquigarrow X = [3 \ 2 \ 1]^T$</p>
C	2	<p>If $A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$, then find the eigen values and eigen vectors corresponding to each eigen value of A. Also, write the eigen space for each eigen values.</p> <p>Answer: $\lambda = -1 \rightsquigarrow X = [-1 \ 1]^T, \quad \lambda = 1 \rightsquigarrow X = [1 \ 1]^T$</p>
C	3	<p>Find the adjacency eigen values and eigen vector for complete graph K_4.</p> <p>Answer: $\lambda = -1, -1, -1, 3$. & Eigen Vector = $[-3 \ 1 \ 1 \ 1]^T$ corresponding to -1 & $[1 \ 1 \ 1 \ 1]^T$ corresponding to 3.</p>
H	4	<p>Find the eigen values of $A = \begin{bmatrix} -5 & 4 & 34 \\ 0 & 0 & 4 \\ 0 & 0 & 4 \end{bmatrix}$. Is it invertible?</p> <p>Answer: $-5, 0, 4$ & No</p>
H	5	<p>Find the eigen values of the matrix</p> $A = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$ <p>Answer: $\lambda = -1, -1, \text{ and } 2$</p>
H	6	<p>Find the Laplacian eigen values and eigen vector for complete graph K_4.</p> <p>Answer: $\lambda = -1, -1, \text{ and } 2$</p>
H	7	<p>Find the Laplacian and adjacency eigen value of P_4 and S_4.</p> <p>Answer: $\lambda = -1, -1, \text{ and } 2$</p>

Method – 4 ↗ Visualization using Eigen vector

Spectral Clustering:

- There are three main types of clustering:
 - (1) Bottom-Up, (2) Assignment-Based, and (3) Top-Down.
- The bottom-up variety was like the hierarchical agglomerative clustering where we start with very small clusters and build bigger clusters.
- The assignment based clustering was like the k-center or the k-means variety where we “assign” each object to a center.
- The third type, top-down clustering, is what we will be discussing here. It starts from one big cluster and gradually divides the big clusters into smaller and smaller clusters.
- Find the best cut of the data into two pieces.
- Recur on both pieces until that data should not be split anymore.
- So how to cluster a graph? A cluster is a subset $S \subset V$.
- We are performing top down clustering, so we only need to consider a subset S and its compliment $\bar{S} = V - S$.
- In general, we want many edges within a cluster (small width), and few edges between clusters (large split).
- The volume of a cluster is $\text{Vol}(S) =$ the number of edges with at least one vertex in V .
- The cut between two clusters S, T is $\text{Cut}(S, T) =$ the number of edges with one vertex in S and the other in T .
- Then we want a large $\text{Vol}(S)$ for each cluster and a small $\text{Cut}(S, T)$ for each pair of clusters.

Steps for Spectral Clustering with normalized Laplacian matrix:

- Start with the Laplacian matrix and find the eigenvector of a matrix.
- There are several eigenvectors of L (the normalized Laplacian): list them sorted by λ (smaller to larger).
- This can be calculated easily in python using the `eigvals`, `V = np.linalg.eigh(L)` command.
- The first eigenvalue of the Laplacian is always 0, up to numerical error.

- The second eigenvector of the normalized Laplacian is a very important descriptor of a graph.
 - It tells us how to best cut the graph.
 - It tells us how “best” to put all of the vertices on a single line. It is called the **Fiedler vector**.
- We can set cluster $S = \{v_i \in V : u_2(v_i) < 0\}$ and cluster $T = V - S$.

More about Spectral Clustering:

- Alternatively, we can use the first d-eigenvectors (scaled by eigenvalues) to embed the vertices in R^d .
- Then we can use any Euclidean clustering algorithm (such as k-means clustering).
- More generally, the adjacency matrix need not be 0–1.
- It can be filled with the similarity value defined by some similarity between element; then A stands for affinity.
- The diagonal is defined as the sum of elements in a row (or column — it must be symmetric). Then spectral clustering can be run as before.
- When the similarity of a pair is very small, it is a good heuristic to round the values down to 0 in the matrix to make the algorithm run faster.

Example of Method-4: Perfect Matching and Hall's Theorem (without proof)

C	1	<p>Find 2 cluster using spectral clustering of following graph.</p> <p>Answer: S = ['a', 'b', 'c', 'd'] and T = ['e', 'f', 'g', 'h'].</p>
H	2	<p>Find 2 cluster using spectral clustering of following graph.</p> <p>Graph vertices: a, b, c, d, e, f, g. Edges: (a,b), (b,c), (c,d), (d,a), (a,c), (e,f), (f,g), (e,g), (c,e), (b,e).</p> <p>Answer: S = ['a', 'b', 'c', 'd'] and T = ['e', 'f', 'g'].</p>

***** End of the Unit *****