

# Spectral Clustering

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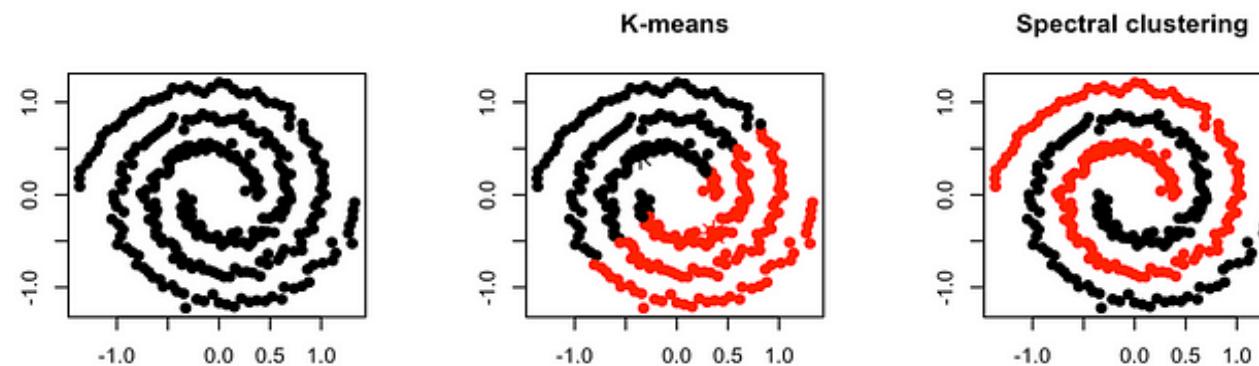
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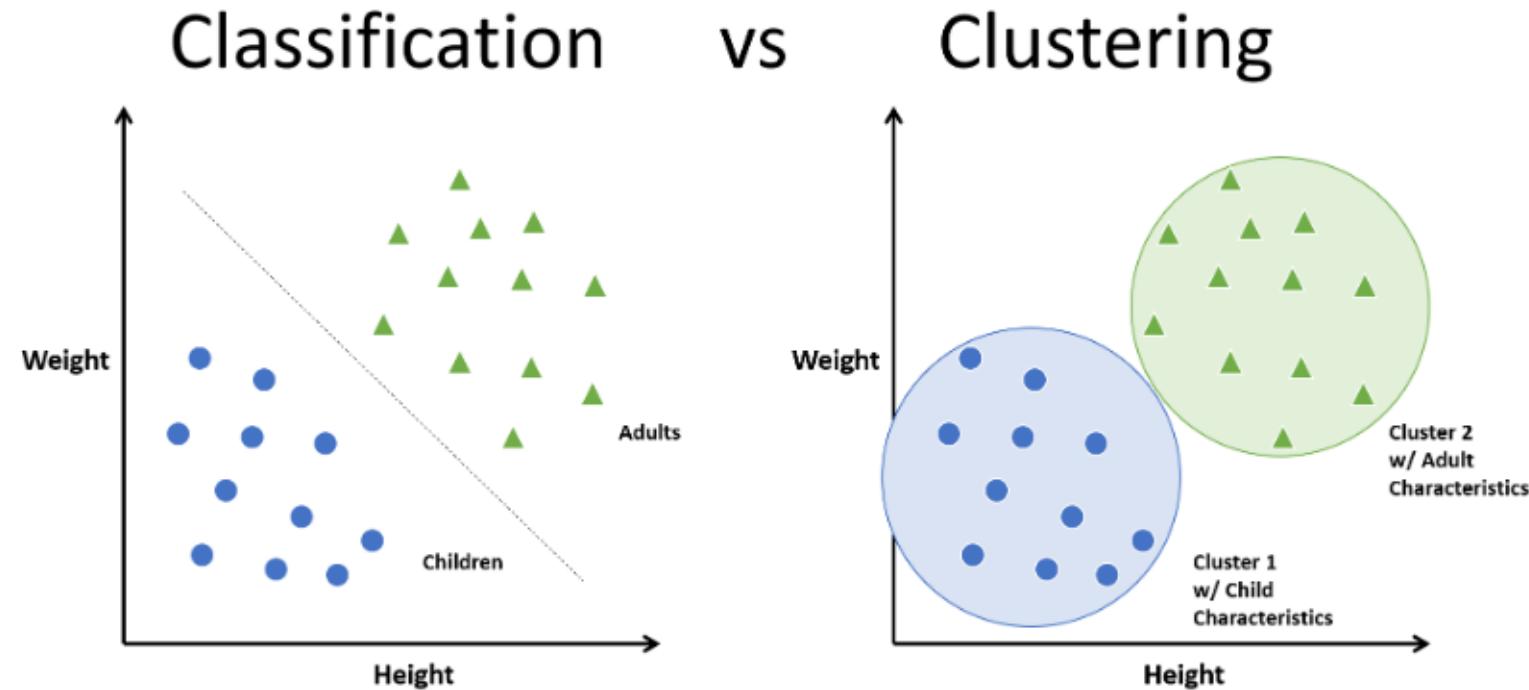
# What is Spectral Clustering?

- Data clustering technique that identifies groups of similar data points by leveraging the eigenvalues and eigenvectors of a similarity graph.
- Two ways to approach clustering:
  - **Compactness:** Points that are in close proximity to one another belong to the same cluster
  - **Connectivity:** Points that are linked or directly adjacent to one another are grouped into the same cluster



Source: <https://tinyurl.com/5ekmrpz2>

# Clustering Vs Classification



Source: <https://tinyurl.com/e5se3zp3>

# Why Spectral Clustering?

Handling  
complex  
cluster shapes

Non-linear  
separability

Graph-based  
representation

Sensitivity to  
connectivity

Community  
detection in  
networks

Image  
segmentation

Dimensionality  
reduction

Unsupervised  
learning

Versatility in  
data

Robustness to  
noise and  
outliers

# Challenges of Traditional Clustering

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Sensitivity to initial centroids

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Assumption of equal-sized cluster

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Assumption of spherical clusters

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Difficulty with non-linear relationships

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Outlier sensitivity

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Influence of noise

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Difficulty with varying clusters densities

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Fixed number of clusters

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Limited capability for graph data

# Process: Affinity Matrix Construction

- Given a dataset with n data points, a matrix A is constructed.
- This matrix encodes the pairwise similarity between data points.
- Common similarity measures include Gaussian similarity (based on a radial basis function) 
$$A_{ij} = \begin{cases} \exp(-d^2(x_i, x_j)/\sigma^2) & i \neq j \\ 0 & i = j \end{cases}$$
- Or k-Nearest Neighbors (where  $A_{ij}$  is non-zero if data points i and j are among the k nearest neighbors of each other).
- Or kernel

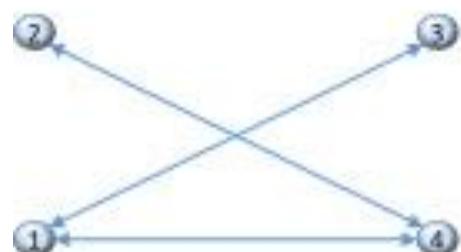
## Process: Degree Matrix

- For each row in the affinity matrix, sum up the values to get the total similarity or degree of connection for each data point.
- The degree matrix  $D$  is a diagonal matrix where each diagonal element represents the degree of the corresponding node in the graph.
- If  $A$  is the affinity matrix, then the degree matrix  $D$  is formulated as  $D_{jj} = \sum_i A_{ij}$ , where  $i$  and  $j$  represent row and column indices, respectively.

# Process: Laplacian Matrix

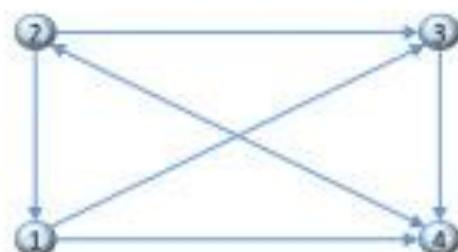
- The Laplacian matrix is derived from a graph, where nodes represent data points, and edges represent the relationships between these points.  $L = D - A$

Graph 1  
undirected graph



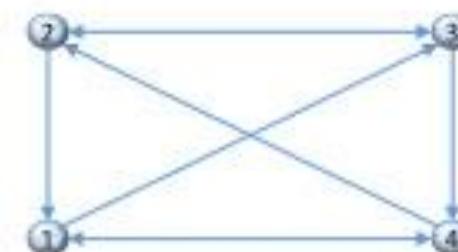
$$L(G) = \begin{bmatrix} 2 & 0 & -1 & -1 \\ 0 & 1 & 0 & -1 \\ -1 & 0 & 1 & 0 \\ -1 & -1 & 0 & 2 \end{bmatrix}$$

Graph 2  
directed graph



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

Graph 3  
balanced directed  
graph



$$L(G) = \begin{bmatrix} 2 & -1 & 0 & -1 \\ 0 & 2 & -1 & -1 \\ -1 & -1 & 2 & 0 \\ -1 & 0 & -1 & 2 \end{bmatrix}$$

Source: <https://tinyurl.com/2t5tz7bx>

# Process: Eigenvalue Problems

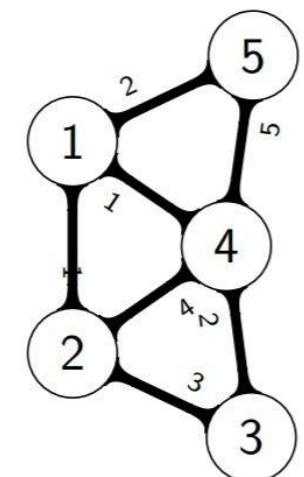
- Eigenvalues characterize the behavior of the linear transformation associated with the matrix.
- In spectral clustering, eigenvalues convey information about the underlying structure and connectivity of the data.
- Smaller eigenvalues correspond to more global patterns, while larger eigenvalues capture finer, more local patterns.

# Process: Eigenvector Calculation

- Solve the  $Lv = \lambda v$  where  $\lambda$  is the eigenvalues and  $v$  is the eigenvectors.
- The eigenvalues are typically sorted in ascending order.
- The selected eigenvectors serve as feature vectors for clustering.

**A** adjacency matrix  
**W** weight matrix  
**D** (diagonal) degree matrix  
**L = D - W** graph **Laplacian** matrix

$$L = \begin{pmatrix} 4 & -1 & 0 & -1 & -2 \\ -1 & 8 & -3 & -4 & 0 \\ 0 & -3 & 5 & -2 & 0 \\ -1 & -4 & -2 & 12 & -5 \\ -2 & 0 & 0 & -5 & 7 \end{pmatrix}$$



Source: <https://tinyurl.com/65sbbx7p>

## Process: Embedding

- By using eigenvectors as features, spectral clustering operates in a reduced-dimensional space, potentially enhancing the separation of clusters.
- The computed eigenvectors serve as a new set of features for the data points.
- Each data point is represented as a vector in this new space, often referred to as the spectral embedding.

# Process: Clustering in Embedded Space

- K-means can then be applied to the embedded data points to group similar data points into clusters.
- These algorithms work in lower-dimensional space defined by the spectral embedding
- It's important to specify the number of clusters ( $k$ ) before applying traditional clustering techniques.
- Assign data point to the cluster with the highest probability based on the output.

# Example

- [https://www.youtube.com/watch?v=rVnOANM0oJE&ab\\_channel=Udacity](https://www.youtube.com/watch?v=rVnOANM0oJE&ab_channel=Udacity)



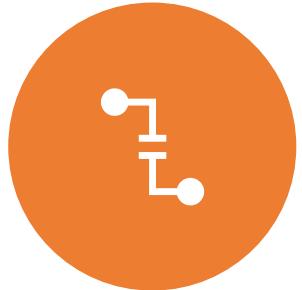
# Advantages of Spectral clustering

Facial Recognition:  
Spectral clustering  
identifies facial patterns  
using similarity  
graphs and eigenvalues.

Advantages Over K-  
means: It excels in  
recognizing complex  
facial patterns and  
handling noise.

High-Dimensional Data:  
Spectral clustering is  
effective in recognizing  
faces in high-  
dimensional feature  
spaces.

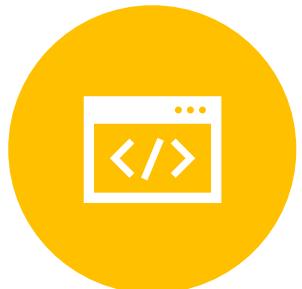
# Disadvantages to Spectral Clustering



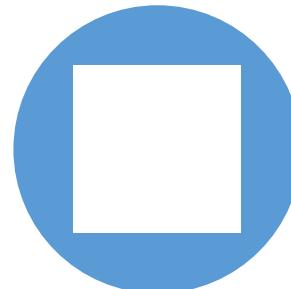
**Parameter Sensitivity:**  
Sensitivity to parameter settings,  
such as the number of clusters.



**High Computational Cost:**  
Computationally intensive,  
particularly for large datasets.



**Limited Scalability in High Dimensions:** May not work well  
in high-dimensional spaces  
without dimensionality reduction



# Applications of Spectral Clustering

Face Clustering

Expression Analysis

Age Estimation

Gender Classification

Face Verification

# Example

- **Scenario:** We have a dataset of images, and we need to group together similar faces
- **Mathematical steps + programming:**
  1. Preprocessing: each  $m$  by  $n$  image is transformed into a  $mn$ -dimensional feature vector
  2. Similarity Matrix Construction: Given  $n$  images, the similarity matrix  $W$  is a  $n \times n$  matrix where  $W_{ij}$  represents the similarity between images  $i$  and  $j$

# Example

- Mathematical steps + programming:

- Code:

```
import numpy as np

def gaussian_similarity(x_i, x_j, sigma):
    return np.exp(-np.linalg.norm(x_i - x_j)**2 / (2 * sigma**2))

def construct_similarity_matrix(X, sigma):
    n = X.shape[0]
    W = np.zeros((n, n))
    for i in range(n):
        for j in range(i, n):
            similarity = gaussian_similarity(X[i], X[j], sigma)
            W[i, j] = similarity
            W[j, i] = similarity # Since W is symmetric
    return W
```

# Example

- **Mathematical steps + programming:**

3. Degree Matrix: Calculate the degree matrix  $D$ , which is a diagonal matrix where  $D_{ii}$  is the degree of data point  $i$ , i.e., the sum of its edge weights

```
def construct_degree_matrix(W):
    return np.diag(np.sum(W, axis=1))
```

4. Laplacian Matrix: Compute the Laplacian matrix  $L = D - W$ .

```
def construct_laplacian_matrix(D, W):
    return D - W
```

# Example

- **Mathematical steps + programming:**

5. Eigenvector Calculation: Compute the first k eigenvectors of the Laplacian matrix.

```
def compute_eigenvectors(L, k):  
    eigenvalues, eigenvectors = np.linalg.eigh(L)  
    return eigenvectors[:, :k]
```

6. Spectral Embedding: The k eigenvectors form the spectral embedding. Each image is represented in the embedded space.

# Example

- **Mathematical steps + programming:**

7. Clustering: Apply a clustering algorithm to the embedded space. For example, use k-means clustering to group the images into k clusters.

```
from sklearn.cluster import KMeans

def cluster_embedding(embedding, k):
    kmeans = KMeans(n_clusters=k, random_state=0).fit(embedding)
    return kmeans.labels_
```

8. Post-Processing and Interpretation: Analyze the clusters to see if they correspond to meaningful groupings of faces. For example, they might represent different individuals.

# Reference

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- [3] “Laplacian matrix,” Laplacian Matrix - an overview | ScienceDirect Topics, <https://www.sciencedirect.com/topics/computer-science/laplacian-matrix> (accessed Nov. 5, 2023).
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# Questions?