CLUSTERING

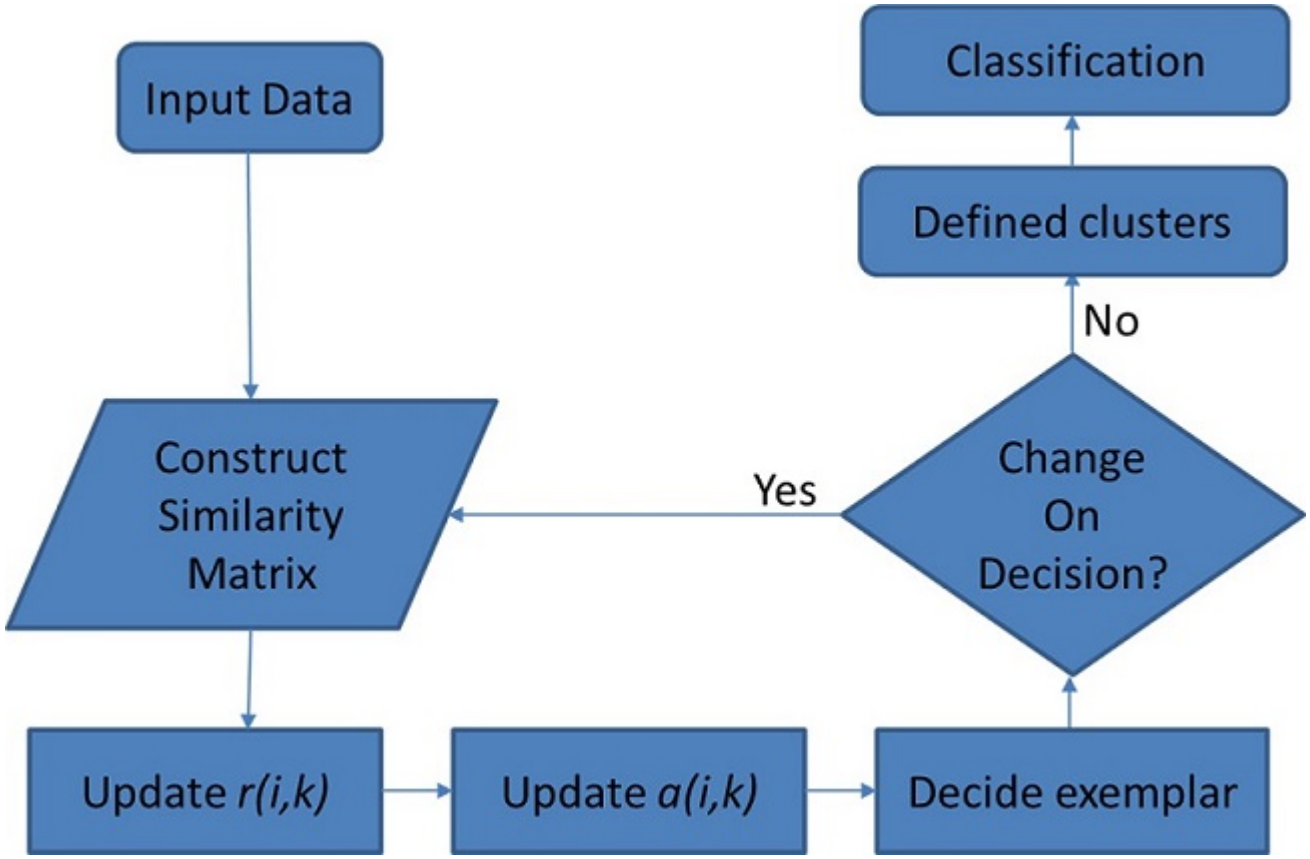
Algorithms Used in Clustering:

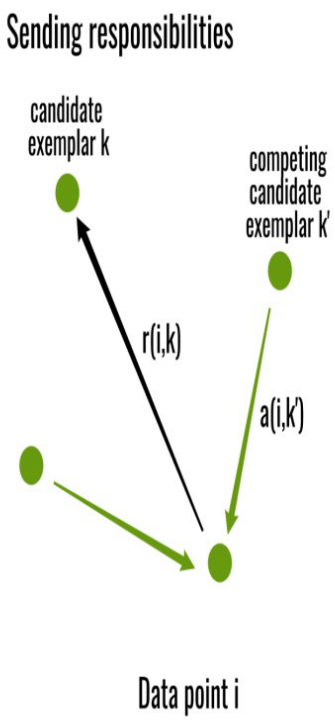
1. **Affinity Propagation**
2. **DBSCAN**
3. **HDBSCAN**
4. **Mean Shift**
5. **Spectral**
6. **Optics**
7. **BIRCH**

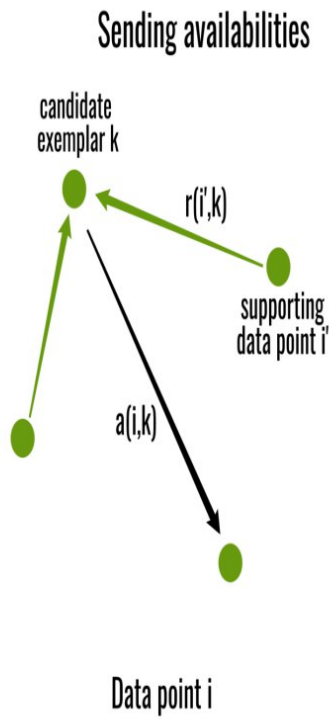
AFFINITY PROPAGATION

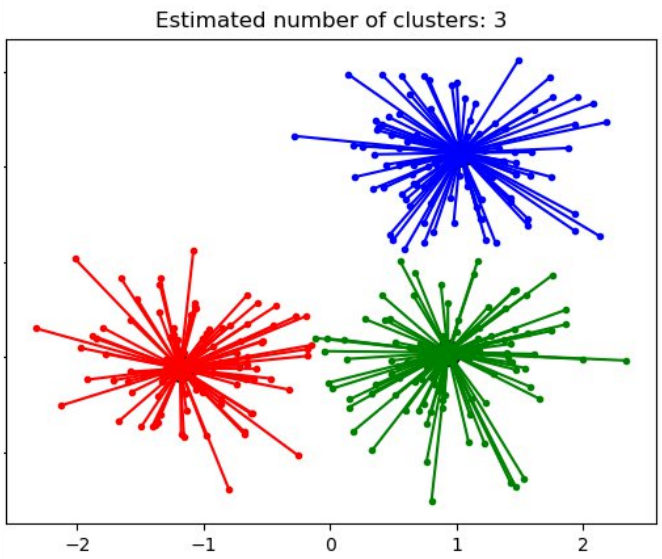
- Affinity Propagation is a clustering method that **groups similar data points together**.
- Unlike other methods like K-Means it **doesn't need you to set the number of clusters**.
- Instead it figures out the number of clusters on its own.
- It allows data points to **communicate with each other by sending messages**.
- These messages help them decide which points should act as leaders.

Flow Diagram for Affinity Propagation




Sending responsibilities
candidate
exemplar k
competing
candidate
exemplar k'
r(i,k)
a(i,k')
Data point i


Sending availabilities
candidate
exemplar k
r(i',k)
supporting
data point i'
a(i,k)
Data point i

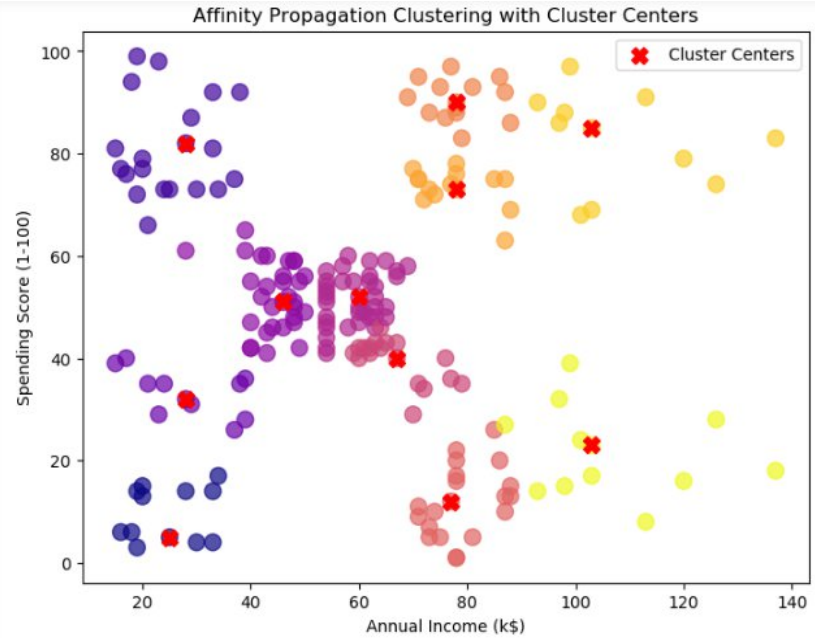

Estimated number of clusters: 3
−2
−1
0
1
2

```
]: from sklearn.cluster import AffinityPropagation
clustering = AffinityPropagation().fit(x)
clustering
```

```
]: AffinityPropagation(affinity='euclidean', convergence_iter=15, copy=True,
                       damping=0.5, max_iter=200, preference=None, verbose=False)
```

```
]: clustering.labels_
```

```
plt.figure(figsize=(8,6))

#Colormap = 'viridis','plasma','coolwarm'
plt.scatter(x[:,0], x[:,1], c=y_pred, cmap='plasma', s=100, alpha=0.7

# Plot cluster centers
plt.scatter(ap.cluster_centers_[:,0], ap.cluster_centers_[:,1],
            c='red', marker='X', s=100, label='Cluster Centers')

plt.title("Affinity Propagation Clustering with Cluster Centers")
plt.xlabel("Annual Income (k$)")
plt.ylabel("Spending Score (1-100)")
plt.legend()
plt.show()
```



DBSCAN(Density Based Spacial Clustering of Applications with Noise)

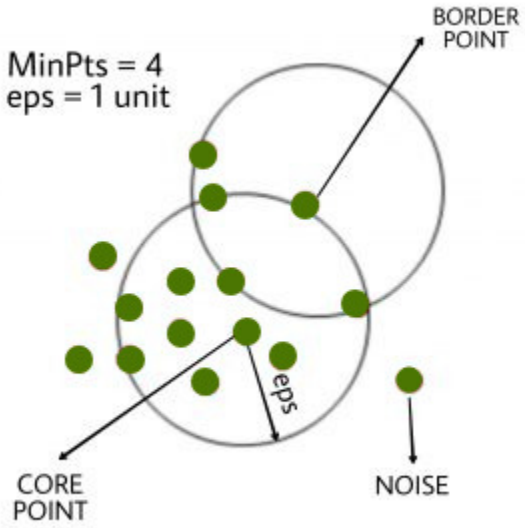
- DBSCAN is a density-based clustering algorithm that groups data points that are closely packed together and marks outliers as noise based on their density in the feature space.
- It identifies clusters as dense regions in the data space separated by areas of lower density.
- Key Parameters : Epsilon(eps), MinPts

How Does DBSCAN Work?

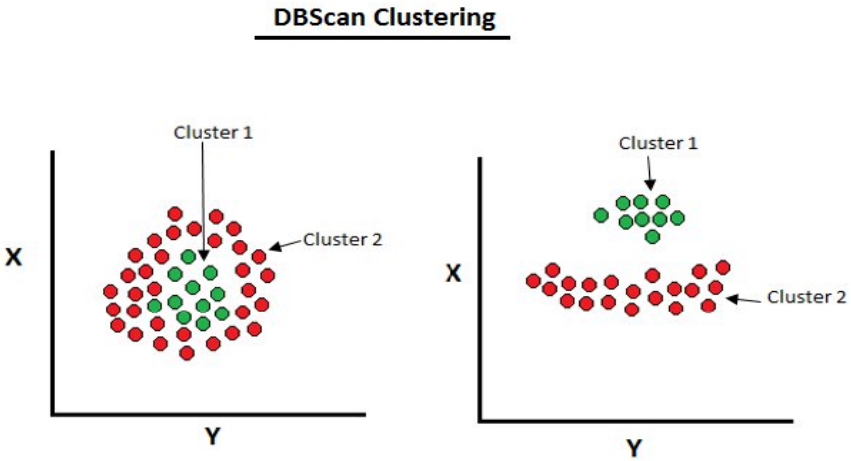
DBSCAN works by categorizing data points into three types:

- Core points which have a sufficient number of neighbors within a specified radius (eplison)
- Border points which are near core points but lack enough neighbors to be core points themselves
- Noise points which do not belong to any cluster.

Steps involved:



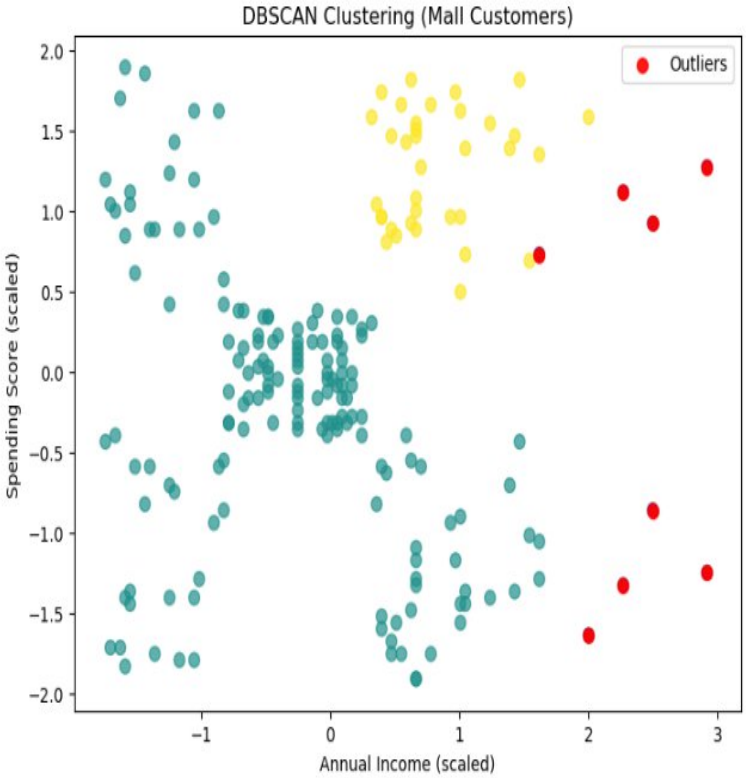
- Identify Core Points
- Form Clusters
- Density Connectivity
- Label Noise Points



```
from sklearn.preprocessing import StandardScaler
sc= StandardScaler()
x = sc.fit_transform(x)
```

```
from sklearn.cluster import DBSCAN
dbscan = DBSCAN(eps=0.5,min_samples=5)
y_dbscan = dbscan.fit_predict(x)
```

```
# plot
plt.figure(figsize=(8,6))
plt.scatter(x[:, 0], x[:, 1], c=y_dbscan, cmap="viridis", s=50, alpha=0.7)

# Highlight outliers (label = -1)
outliers = (y_dbscan == -1)
plt.scatter(x[outliers, 0], x[outliers, 1],c="red", s=50, alpha=0.9, label="Outliers

plt.title("DBSCAN Clustering (Mall Customers)")
plt.xlabel("Annual Income (scaled)")
plt.ylabel("Spending Score (scaled)")
plt.legend()
plt.show()
```

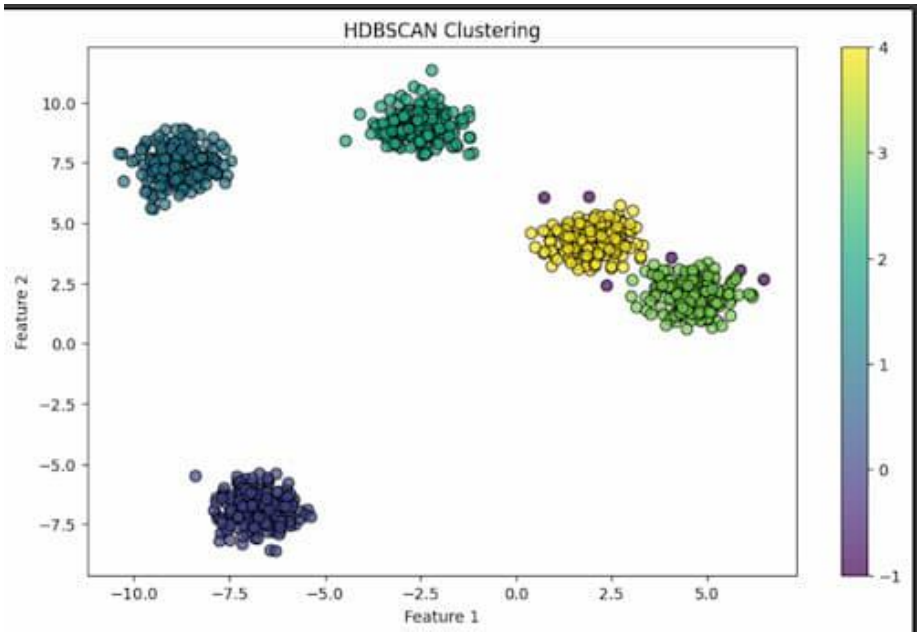


Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN)

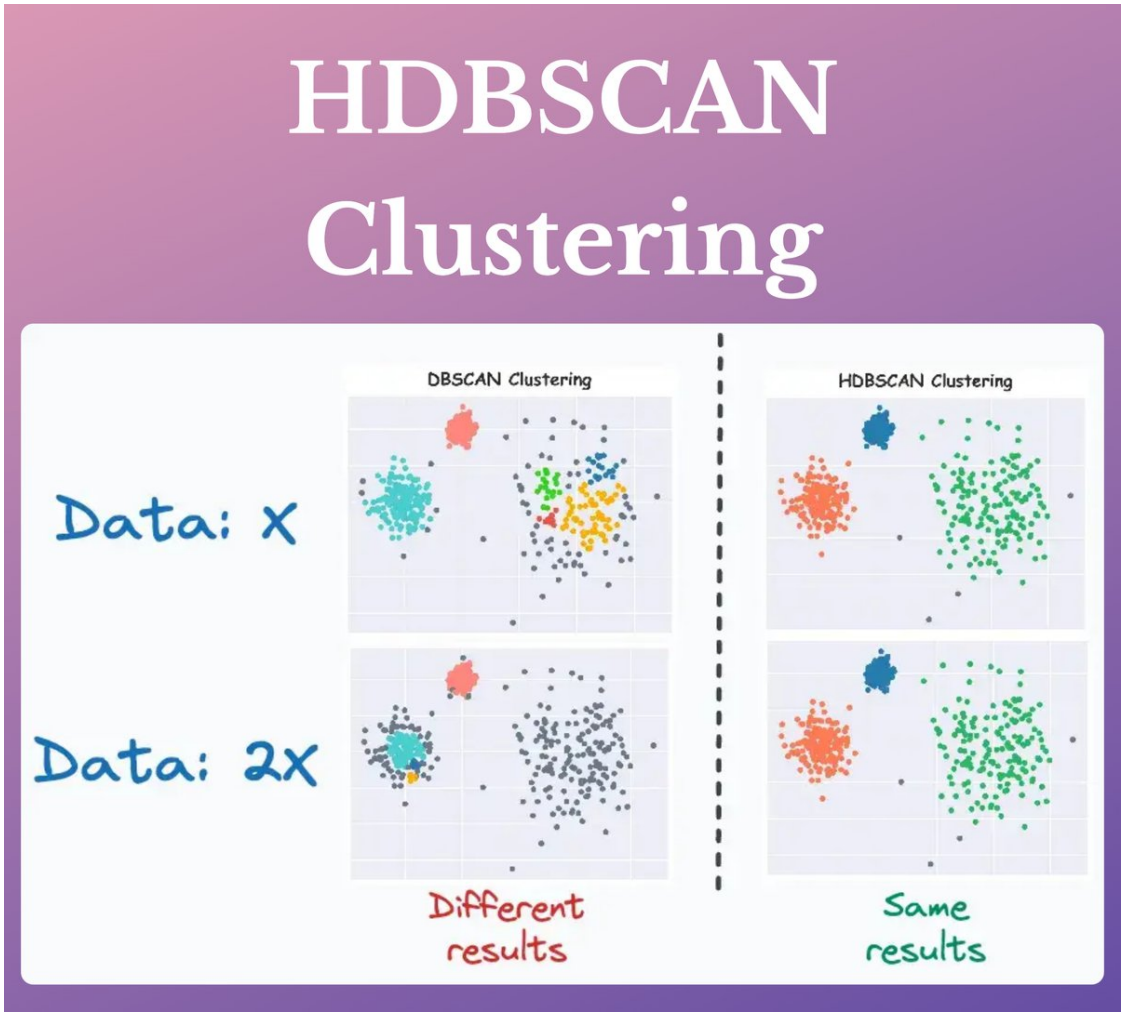
- HDBSCAN is a clustering algorithm that is designed to uncover clusters in datasets based on the density distribution of data points.
- Unlike some other clustering methods, it doesn't requires specifying the number of clusters in advance, making it more adaptable to different datasets.
- It uses high-density regions to identify clusters and views isolated or low-density points as noise.
- HDBSCAN is especially helpful for datasets with complex structures or varying.
- **Important Parameters :** 'min_cluster_size‘, 'min_samples‘, 'cluster_selection_epsilon‘, 'metric‘, 'cluster_selection_method‘, 'alpha, 'gen_min_span_tree, metric_params, algorithm, core_distance_n_jobs, allow_single_cluster

Libraries used:

- The necessary libraries that includes numpy, matplolib, hdbscan and metrics like silhouette_score, adjusted rand index for evaluating the metrics.

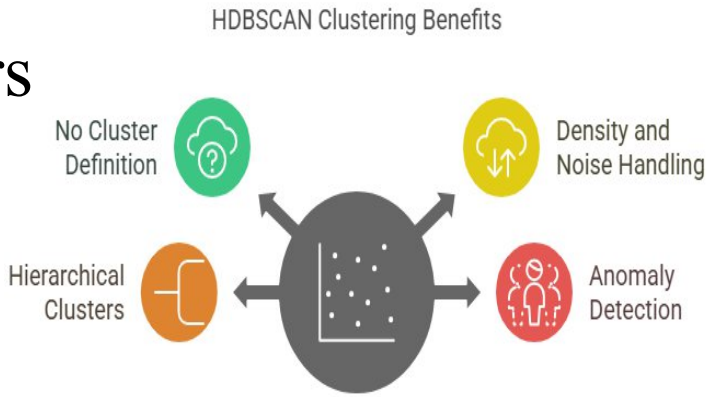


Differences between DB & HDB:



Advantages:

- Automatic cluster Discovery
- Handling Cluster Shapes
- Robust to noise and outliers
- Scalability



Disadvantages:

- Computationally Intensive
- Sensitive to Distance metric
- Parameter Sensitivity

Mean Shift Algorithm:

- Mean-shift clustering is a non-parametric, density-based clustering algorithm that can be used to identify clusters in a dataset.
- The basic idea behind mean-shift clustering is to shift each data point towards the mode (i.e., the highest density) of the distribution of points within a certain radius.
- The algorithm iteratively performs these shifts until the points converge to a local maximum of the density function. These local maxima represent the clusters in the data.

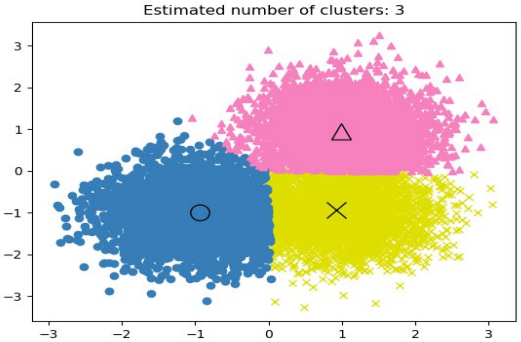
Process of mean-shift clustering algorithm

Advantages:

Disadvantages:

- It doesn’t requires number of cluster to be specified.
- It doesn’t make any assumptions about distribution of data.
- Model-free, doesn't assume any prior shape like spherical, elliptical, etc. on data clusters

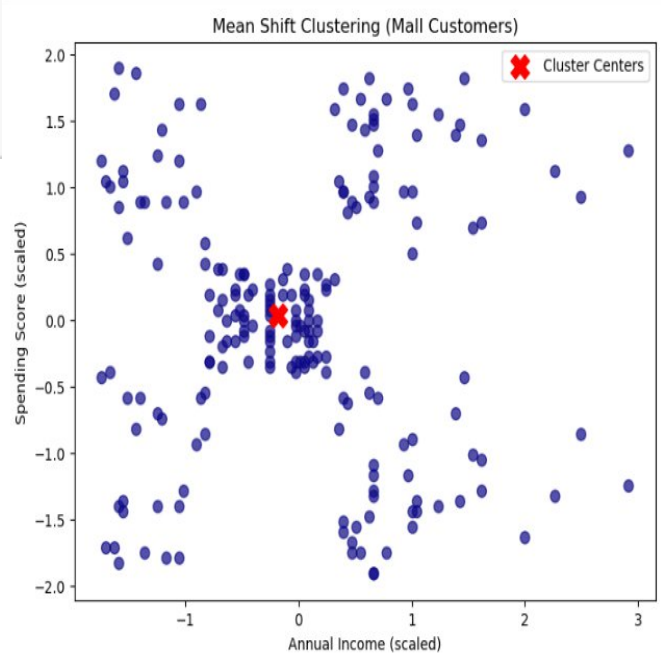
- Output depends on window size
- Computationally (relatively) expensive (approx 2s/image)
- Doesn't scale well with dimension of



```python
from sklearn.preprocessing import StandardScaler
sc= StandardScaler()
x_scaler = sc.fit_transform(x)
```

```python
from sklearn.cluster import MeanShift
ms = MeanShift()
y_ms = ms.fit_predict(x_scaler)
```

```python
# Plot clusters
plt.figure(figsize=(8,6))
plt.scatter(x_scaler[:,0], x_scaler[:,1], c=y_ms, cmap='plasma', s=50, alpha=0.7)

# Plot cluster centers
plt.scatter(ms.cluster_centers_[:,0], ms.cluster_centers_[:,1],
            c='red', marker='X', s=200, label='Cluster Centers')

plt.title("Mean Shift Clustering (Mall Customers)")
plt.xlabel("Annual Income (scaled)")
plt.ylabel("Spending Score (scaled)")
plt.legend()
plt.show()
```



OPTICS (Ordering Points To Identify the Clustering Structure)

- OPTICS (Ordering Points To Identify the Clustering Structure) is a density-based clustering algorithm similar to DBSCAN clustering.
- Unlike DBSCAN which struggles with varying densities.
- OPTICS does not directly assign clusters but instead creates a reachability plot which visually represents clusters.

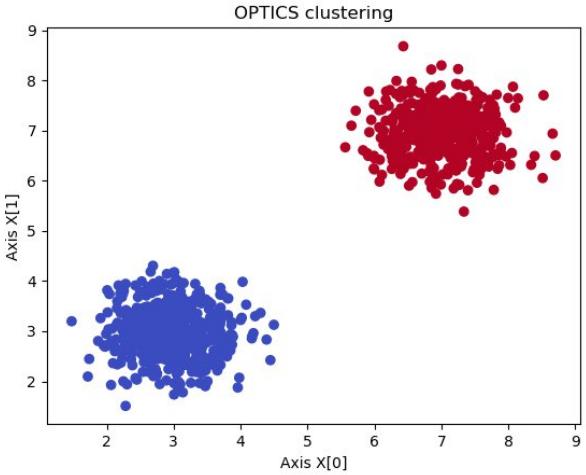
Reachability Plot

- A reachability plot is a graph that helps visualize clustering structures.
- It shows the reachability distance of each point in the dataset. It makes it ordered way based on how OPTICS processes them.

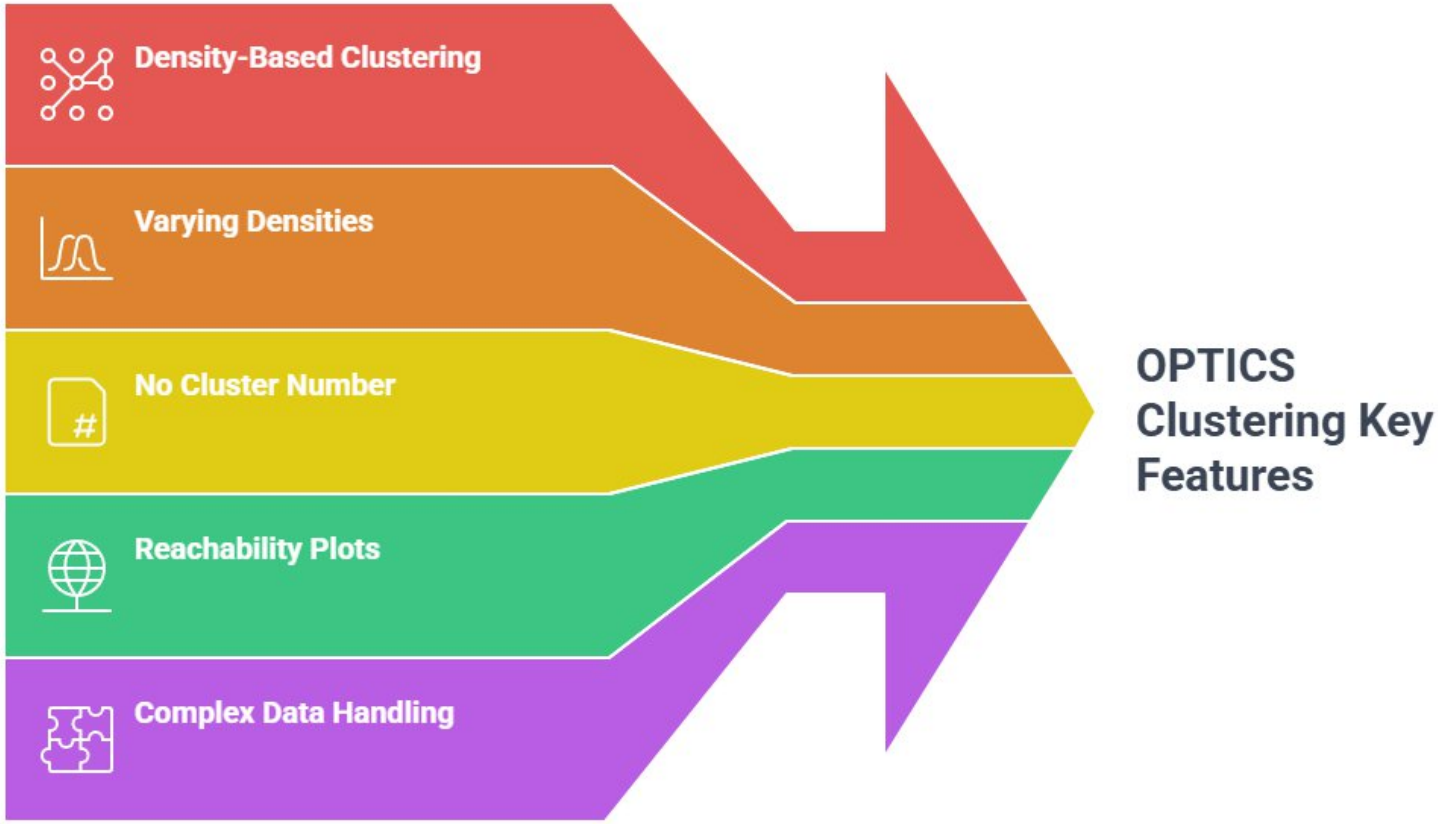
Key concepts in OPTICS:

- **Core Distance** - Minimum distance needed for a point
- **Reachability Distance -** It is a measure of how difficult it is to reach from one point to another

OPTICS Algorithm Process



OPTICS Clustering Overview

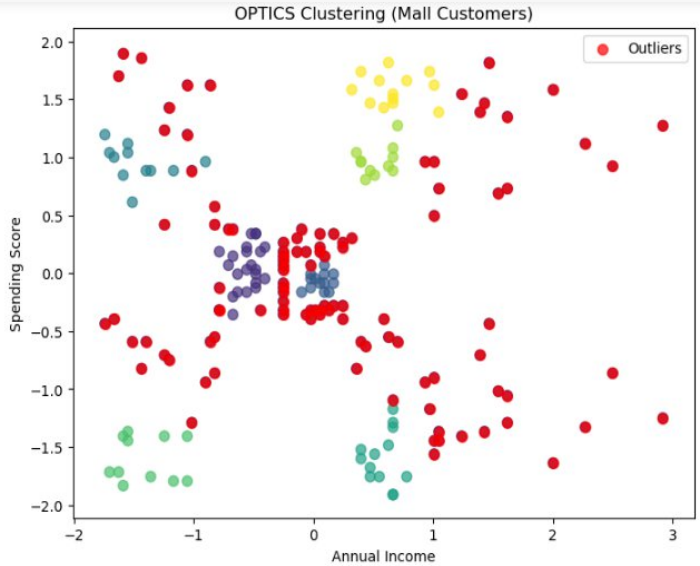


OPTICS Clustering

Pros	Cons
No cluster count	High computation
Varying densities	Distance sensitivity
Noise detection	Large data issues
Diverse shapes	Parameter tuning
Reachability plots	

```
]: from sklearn.cluster import OPTICS
optics = OPTICS(min_samples=5, xi=0.05, min_cluster_size=0.05)
y_optics = optics.fit_predict(x_scaler)
```

```
: # Plot clusters
plt.figure(figsize=(8,6))
plt.scatter(x_scaler[:,0], x_scaler[:,1], c=y_optics, cmap='viridis', s=50, alpha=0.7)

# Highlight outliers (label = -1)
outliers = (y_optics == -1)
plt.scatter(x_scaler[outliers,0], x_scaler[outliers,1], c='red', s=50, alpha=0.7, label='Outliers')

plt.title("OPTICS Clustering (Mall Customers)")
plt.xlabel("Annual Income")
plt.ylabel("Spending Score")
plt.legend()
plt.show()
```



BIRCH(Balanced Iterative Reducing and Clustering using Hierarchies) Algorithm:

- **BIRCH** is a clustering algorithm that can cluster large datasets by first generating a small and compact summary of the large dataset that retains as much information as possible.
- This smaller summary is then clustered instead of clustering the larger dataset.
- BIRCH is often used to complement other clustering algorithms by creating a summary of the dataset that the other clustering algorithm can now use.

Drawback:

- BIRCH has one major drawback - it can only process metric attributes.

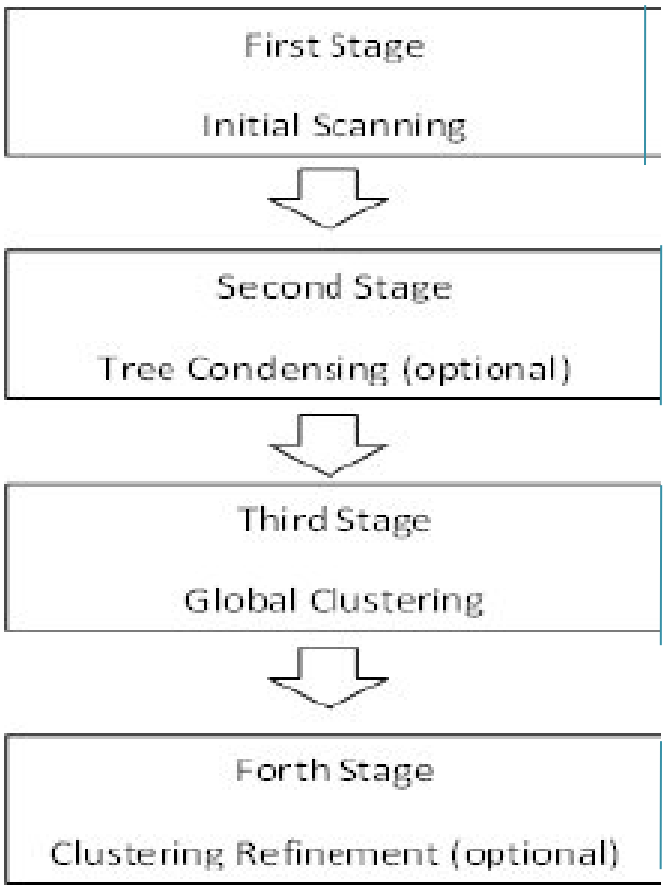
Two important terms:

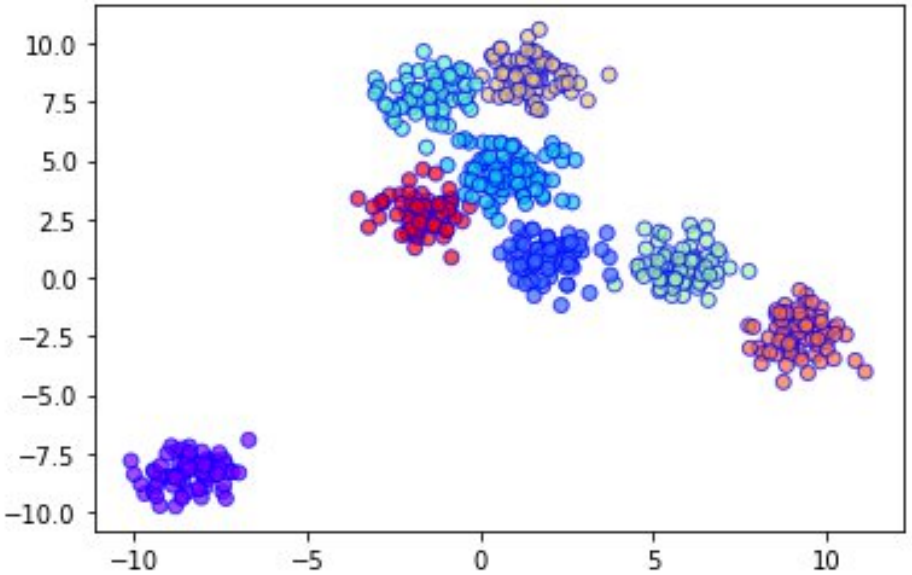
- **Clustering Feature (CF):** BIRCH summarizes large datasets into smaller, dense regions called Clustering Feature (CF) entries.
- **CF – Tree** : A CF tree is a tree where each leaf node contains a sub-cluster.

Parameters of BIRCH Algorithm :

1. **Threshold**
2. **branching_factor**
3. **n_clusters**

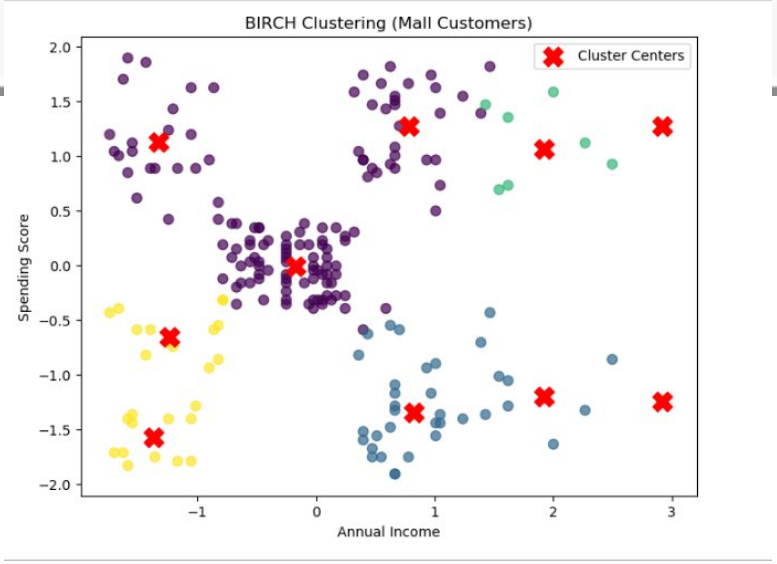
BIRCH Algorithm Process:





```python
from sklearn.cluster import Birch
birch = Birch(n_clusters =4)
y_birch = birch.fit_predict(x_scaler)
```

```python
# Plot clusters
plt.figure(figsize=(8,6))
plt.scatter(x_scaler[:,0], x_scaler[:,1], c=y_birch, cmap='viridis', s=50, alpha=0.7)

# Subclusters plot
if hasattr(birch, 'subcluster_centers_'):  #hasattr = allows us to check whether it has specific attributes or not.
    plt.scatter(birch.subcluster_centers_[:,0], birch.subcluster_centers_[:,1], c='red', marker='X', s=200, label='Cluster Cent

plt.title("BIRCH Clustering (Mall Customers)")
plt.xlabel("Annual Income")
plt.ylabel("Spending Score")
plt.legend()
plt.show()
```



Gaussian Mixture Model

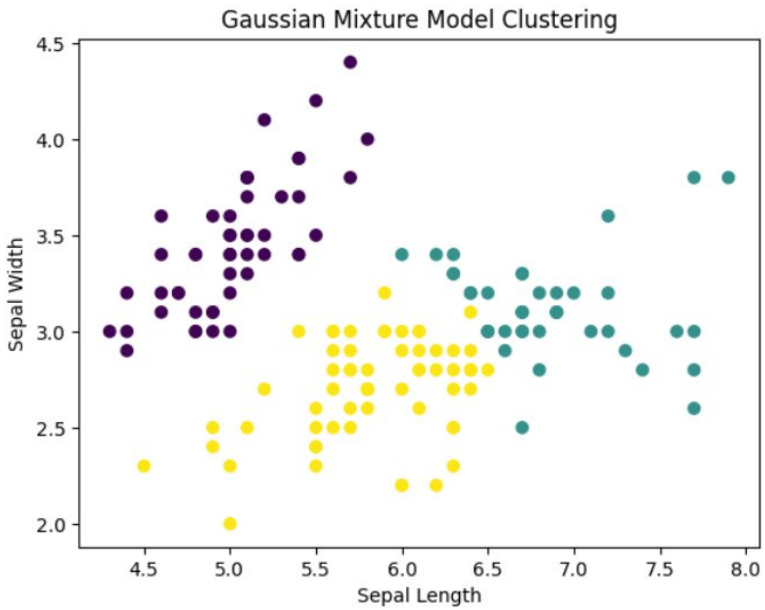
- Gaussian Mixture Model is a probabilistic model that assumes all data points are generated from a mixture of several Gaussian distributions with unknown parameters.
- GMMs perform soft clustering meaning each data point belongs to multiple clusters with certain probabilities.
- Each Gaussian in the mixture is defined by:
  - **Mean (μ)**: The center of the distribution.
  - **Covariance (Σ)**: Describes the spread and orientation.
  - **Mixing coefficient (π)**: Represents the proportion of each Gaussian in the mixture.

Steps involved:

- Gaussian works in two main steps:

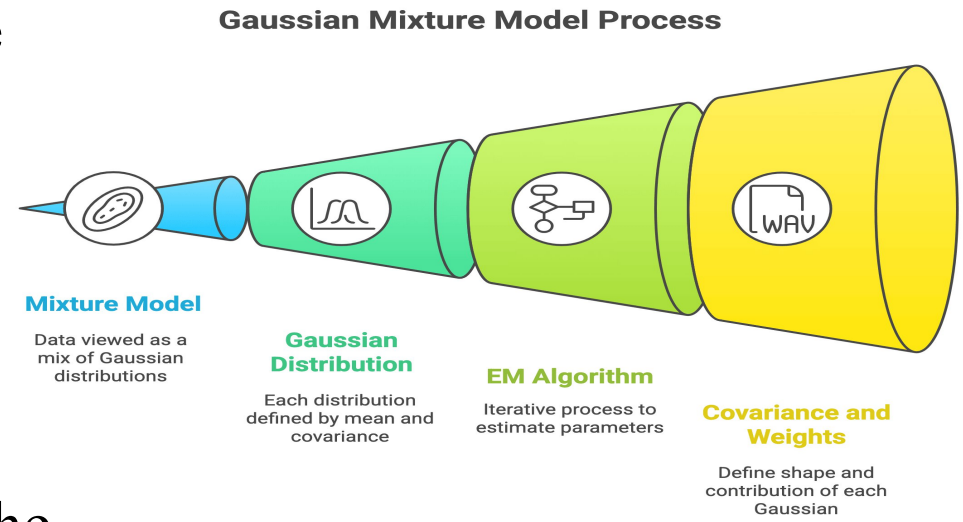
  i) Expectation Step (E-step): In this step the algorithm calculates the probability that each data point belongs to each cluster based on the current parameter estimates (mean, covariance, mixing coefficients).

  ii) Maximization Step (M-step): After estimating the probabilities the algorithm updates the parameters (mean, covariance and mixing coefficients) to better fit the data.

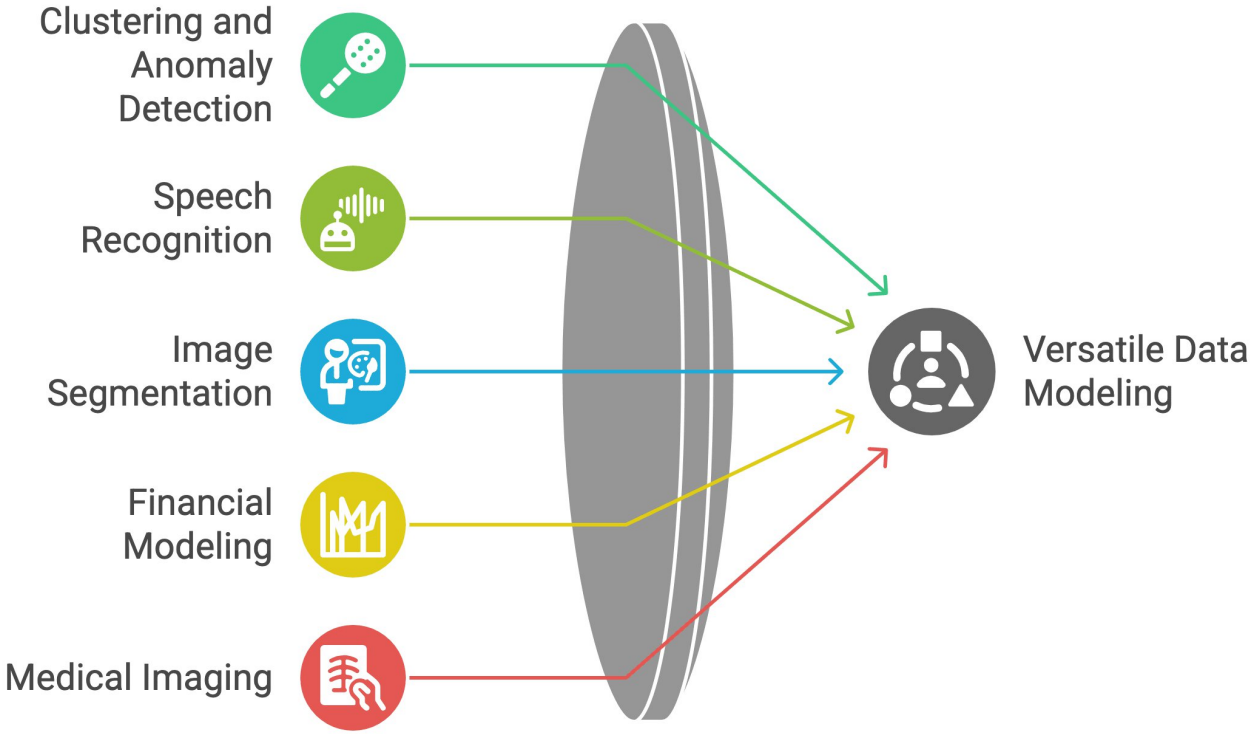


Simple breakdown of the GMM process:

- **Initialization -** Start with initial guesses
- **E-step -** calculate the probability of each cluster.
- **M-step -** Update the parameters.
- **Repeat -** Continue alternating between the E-step and M-step

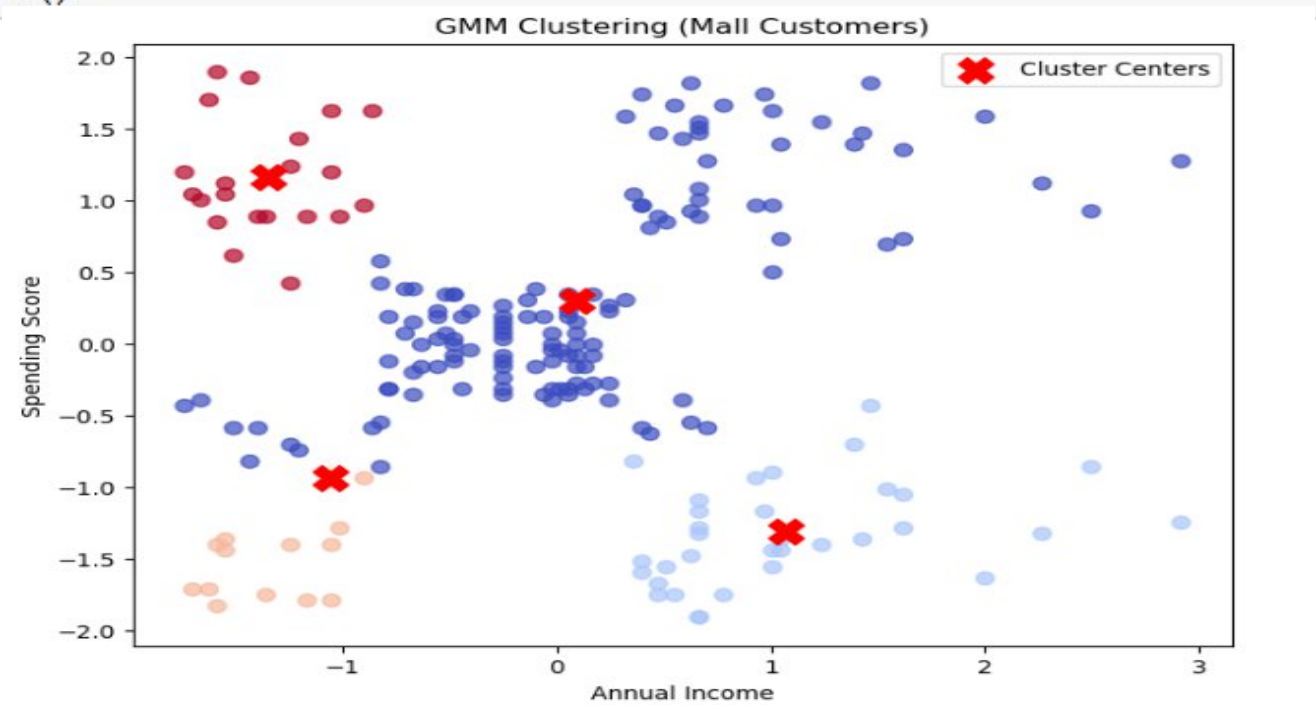


Unified Applications of Gaussian Mixture Models



```
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=4, random_state=42)
y_gmm = gmm.fit_predict(x_scaler)
```

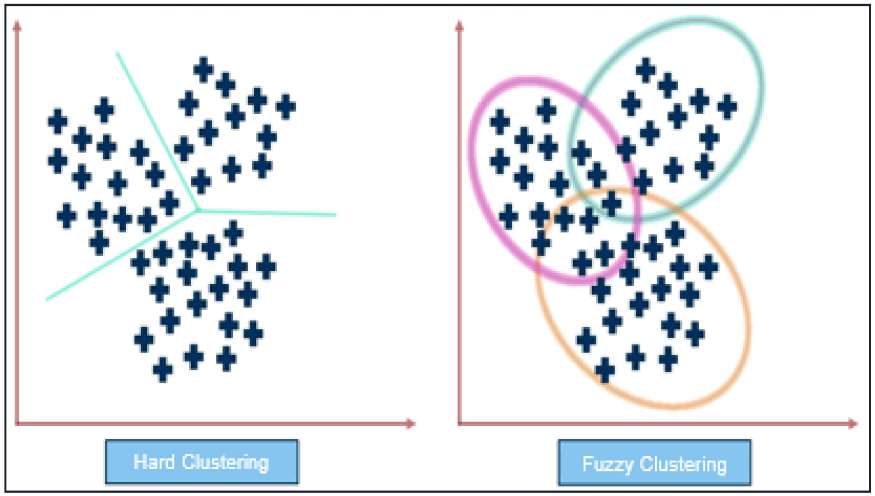
```
# Plot clusters
plt.figure(figsize=(8,6))
plt.scatter(x_scaler[:,0], x_scaler[:,1], c=y_gmm, cmap='coolwarm', s=50, alpha=0.7)

# Highlight Cluster centers
plt.scatter(gmm.means_[:,0], gmm.means_[:,1], c='red', marker='X', s=200, label='Cluster Centers')
plt.title("GMM Clustering (Mall Customers)")
plt.xlabel("Annual Income")
plt.ylabel("Spending Score")
plt.legend()
plt.show()
```



Fuzzy Clustering

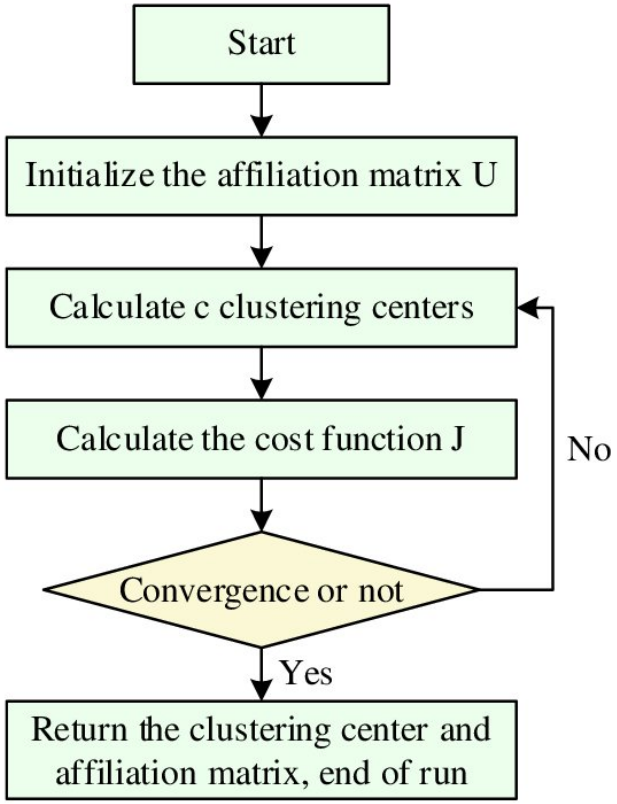
- Fuzzy Clustering also known as soft clustering, is a type of unsupervised machine learning that allows data points belonging to multiple clusters with varying degrees of membership.
- It assigns membership values between 0 and 1 for every cluster.
- It indicates the degree to which a data points belongs to a particular cluster.

- Unlike traditional clustering (like K-Means) where each data points belongs to only one cluster.



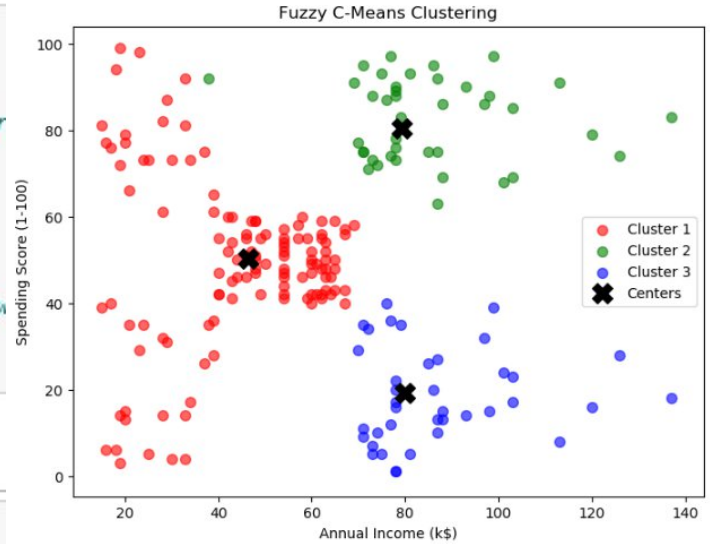
Steps involved in this algorithm:

1. Initialize membership values randomly
2. Compute cluster centroids
3. Calculate distance between Data points and Centroids
4. Update membership values
5. Repeat until convergence
6. Defuzzification(optional)



```python
import skfuzzy as fuzz
n_clusters = 3
cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
    X_scaled.T,          # transpose because skfuzzy expects featur
    c=n_clusters,        # number of clusters
    m=2,                 # fuzziness parameter
    error=0.005,         # stopping criterion
    maxiter=1000,        # max iterations
    init=None)
print("Labels shape:", labels.shape)   # should match number of row
print("Fuzzy Partition Coefficient (FPC):", fpc)
```

```
Labels shape: (200,)
Fuzzy Partition Coefficient (FPC): 0.6802115367982321
```




```python
labels = np.argmax(u, axis=0)
plt.figure(figsize=(8,6))
colors = ['red', 'green', 'blue']  # add more if more clusters

for j, color in enumerate(colors[:n_clusters]):
    plt.scatter(X[labels == j, 0], X[labels == j, 1],c=color,label=f"Cluster {j+1}",s=50, alpha=0.6)

# Rescale cluster centers back to original space
centers = scaler.inverse_transform(cntr)
plt.scatter(
    centers[:, 0], centers[:, 1],c='black', marker='X', s=200, label='Centers'
)

plt.xlabel("Annual Income (k$)")
plt.ylabel("Spending Score (1-100)")
plt.title("Fuzzy C-Means Clustering")
plt.legend()
plt.show()
```

GitHub Link:

https://github.com/Geetharani-CodeAI/Clustering-Algorithm