

UNIT- 4

Unsupervised Learning

Study Guide

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1. Unsupervised Learning

Unsupervised learning deals with discovering patterns, structures, and relationships in unlabeled data.

1.1 Types of Unsupervised Learning

Type	Description	Examples
Clustering	Grouping similar data points	K-means, DBSCAN
Dimensionality Reduction	Reducing features while preserving structure	PCA
Association	Finding rule-based relationships	Apriori

2. Clustering Basics

Clustering aims to group similar data points based on distance or density.

2.1 Partition-Based Clustering

Divides data into a fixed number of clusters.

K-Means Clustering.

Assigns points to the nearest centroid

Recomputes centroids iteratively

Algorithm Steps:

1. Choose k cluster centroids
2. Assign each point to the nearest centroid
3. Recalculate centroid of each cluster
4. Repeat until convergence

Figure: K-Means Workflow

Data Points → Choose k → Assign Points → Update Centroids → Repeat

Advantages: Simple, fast

Disadvantages: Needs k, sensitive to outliers

2.2 K-Modes Clustering

Used for categorical data.

Replaces mean with mode

Uses Hamming distance instead of Euclidean distance

Table: K-Means vs K-Modes

Feature	K-Means	K-Modes
Data Type	Numerical	Categorical
Distance	Euclidean	Hamming

Centroid	Mean	Mode
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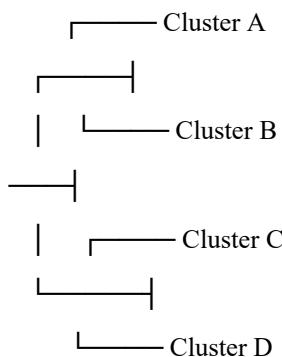
2.3 Hierarchical Clustering

Builds a cluster tree (dendrogram).

Types:

- 1) Agglomerative (bottom-up)
- 2) Divisive (top-down)

Figure: Dendrogram Example



Distance Linkage Methods:

- 1. Single linkage
- 2. Complete linkage
- 3. Average linkage

2.4 Density-Based Clustering (DBSCAN)

Forms clusters using dense regions of points.

Key Concepts:

Core Point: Minimum points within radius

Border Point: Near a core point

Noise: Sparse points

Diagram: DBSCAN Concept

● = Core Point

○ = Border Point

x = Noise

```
●●●○    x   ●●  
●●○○○    ●●
```

Advantages: Detects arbitrarily shaped clusters

Disadvantages: Difficult to tune parameters

3. Self-Organizing Maps (SOM)

Neural-network-based clustering method mapping high-dimensional data to 2D grid.

Components:

- Input layer
- Output grid (usually 2D)

Workflow Diagram:

Input → Best Matching Unit → Update Neighboring Neurons → Repeat

Applications:

- Visualizing high-dimensional data
- Market segmentation

4. Expectation Maximization (EM)

Used in probabilistic clustering.

Often applied to Gaussian Mixture Models (GMMs).

Steps:

1. Expectation (E-step): Estimate probability of each point belonging to clusters
2. Maximization (M-step): Update parameters (means, variance)

Figure: EM Loop

E-Step → Update probs → M-Step → Update parameters → Repeat

5. Principal Component Analysis (PCA)

Used for dimensionality reduction.

Process:

1. Standardize data
2. Compute covariance matrix
3. Compute eigenvectors/eigenvalues
4. Select top components

Diagram: PCA Transformation

Original Axes → Rotate Axes → New PC1 & PC2

Table: PCA Uses

Use Case	Benefit
Visualization	Reduce to 2D/3D
Noise Removal	Drop low-variance components

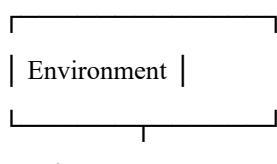
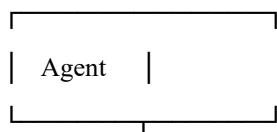
6. Reinforcement Learning

Learning by interacting with environment.

Key Elements:

Element	Description
Agent	Learner/decision maker
Environment	World where agent interacts
Action	Moves taken by agent
Reward	Feedback signal
Policy	Strategy

Diagram: RL Loop



Types of RL:

1. Model-free: Q-learning, SARSA
2. Model-based: Uses learned environment model

• **Additional Diagrams, Examples, and Solved Problems**

1. K-Means – Solved Numerical Example

Dataset: Points: (1,1), (2,1), (4,3), (5,4)

Step 1: Choose k = 2 and initialize centroids

$$C1 = (1,1)$$

$$C2 = (5,4)$$

Step 2: Assign points to nearest centroid

Point	Dist to C1	Dist to C2	Cluster
(1,1)	0	5	C1
(2,1)	1	4.24	C1

(4,3)	3.61	1.41	C2
(5,4)	5	0	C2

Step 3: Recompute centroids

$$C1 = \text{mean}((1,1),(2,1)) = (1.5,1)$$

$$C2 = \text{mean}((4,3),(5,4)) = (4.5,3.5)$$

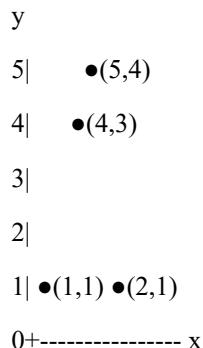
Step 4: Reassign (converges after one more iteration)

Final Clusters:

Cluster 1: (1,1),(2,1)

Cluster 2: (4,3),(5,4)

Diagram:



2. Hierarchical Clustering – Example

Dataset: A(1), B(2), C(8), D(9)

Distances:

$$A-B = 1$$

$$C-D = 1$$

$$B-C = 6$$

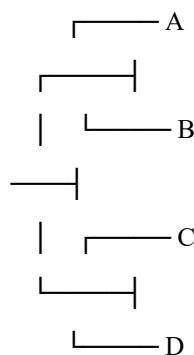
Process:

Merge A & B

Merge C & D

Merge (AB) & (CD)

Dendrogram:



3. DBSCAN Example

Parameters: $\text{eps} = 1.5$, $\text{minPts} = 3$

Dataset: Points forming 2 dense blobs + 1 isolated point.

Result:

Two clusters detected based on density

Outlier marked as noise

Diagram:



Where:

● = core points

○ = border points

x = noise

4. Self-Organizing Map (SOM) – Example

Dataset: Features of animals (size, speed)

SOM Grid Result:

+-----+	+-----+	+-----+
Cat Dog Wolf		
+-----+	+-----+	+-----+
Sparrow Parrot Hawk		
+-----+	+-----+	+-----+

Animals with similar characteristics cluster together.

5. Expectation-Maximization – Numerical Example (Simplified)

Data: 1D points = {1, 2, 8, 9} Assume 2 Gaussians.

Initialization:

Means: $\mu_1=2$, $\mu_2=8$

E-Step: Assign soft probabilities based on distance.

M-Step: Update means:

$$\mu_1 = \text{mean}(1,2) = 1.5$$

$$\mu_2 = \text{mean}(8,9) = 8.5$$

Repeat until convergence.

6. PCA – Worked Example

Dataset:

X	Y
2	0
0	2

Step 1: Compute covariance $\text{Var}(X)=2$, $\text{Var}(Y)=2$, $\text{Cov}(X,Y)=0$

Step 2: Eigenvalues = 2,2 (axes equally important)

Step 3: Principal components = X and Y axes

Diagram:

Original Axes = PCA Axes (since uncorrelated)

7. Reinforcement Learning Example

Agent navigating a grid to reach a goal.

Grid:

$S \rightarrow \square \rightarrow \square \rightarrow G$

S = Start, G = Goal

Rewards:

Move = -1

Reach goal = +10

Q-learning update: $Q(s,a) = Q + \alpha(r + \gamma \max Q' - Q)$

After multiple episodes, the agent learns shortest path.

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