

Additional Topics

In Machine Learning



Association Rule Learning



Additional Topics In Machine Learning

Association Rule Learning

Association Rule Learning is a machine learning technique used to discover **relationships between variables in large datasets**.

It is widely used in market basket analysis, recommendation systems, and fraud detection.

It is a rule-based approach that identifies frequent patterns, correlations, or associations in data.

- Helps uncover hidden insights that may not be obvious through traditional analysis.

Typically expressed in IF-THEN rules:

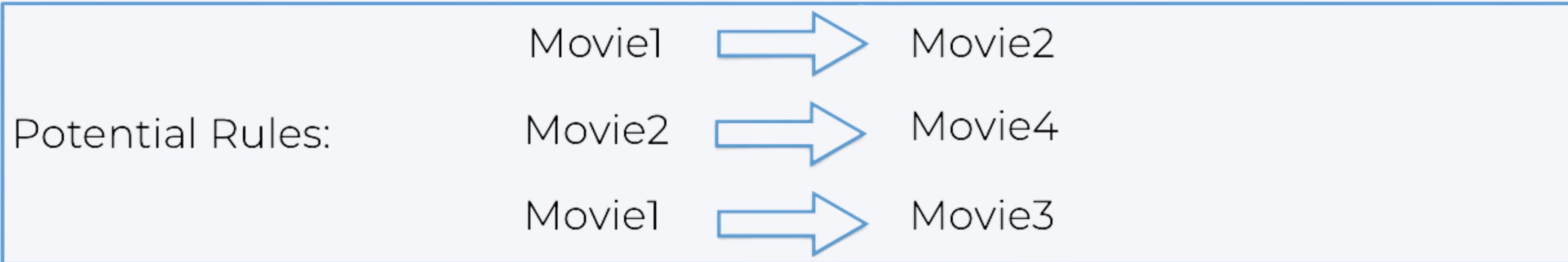
- **Example: IF a customer buys bread, THEN they are likely to buy butter.**

Additional Topics In Machine Learning



Association Rule Learning - Movie Recommendation

User ID	Movies liked
46578	Movie1, Movie2, Movie3, Movie4
98989	Movie1, Movie2
71527	Movie1, Movie2, Movie4
78981	Movie1, Movie2
89192	Movie2, Movie4
61557	Movie1, Movie3



Additional Topics In Machine Learning



Association Rule Learning - Market Basket Optimization

Transaction ID	Products purchased
46578	Burgers, French Fries, Vegetables
98989	Burgers, French Fries, Ketchup
71527	Vegetables, Fruits
78981	Pasta, Fruits, Butter, Vegetables
89192	Burgers, Pasta, French Fries
61557	Fruits, Orange Juice, Vegetables
87923	Burgers, French Fries, Ketchup, Mayo



Association Rule Learning models:

Apriori Algorithm

- A popular association rule learning algorithm.
- Uses a breadth-first search and the "Apriori property" (if an itemset is frequent, its subsets must also be frequent).
- Iteratively expands frequent itemsets to find strong associations.
- Efficient for large datasets but can be slow due to multiple scans of the database.
- Example: Finding frequent product combinations in market basket analysis.

ECLAT

(Equivalence Class Clustering and Bottom-Up Lattice Traversal)

- A faster alternative to Apriori, using a depth-first search approach.
- Stores transactions in vertical format (lists of item occurrences), reducing database scans.
- Works well with dense datasets but struggles with very large itemsets.
- Example: Used in recommendation systems and fraud detection.

Additional Topics In Machine Learning

APriori - Support

Movie Recommendation:

$$\text{support}(\mathbf{M}) = \frac{\# \text{ user watchlists containing } \mathbf{M}}{\# \text{ user watchlists}}$$

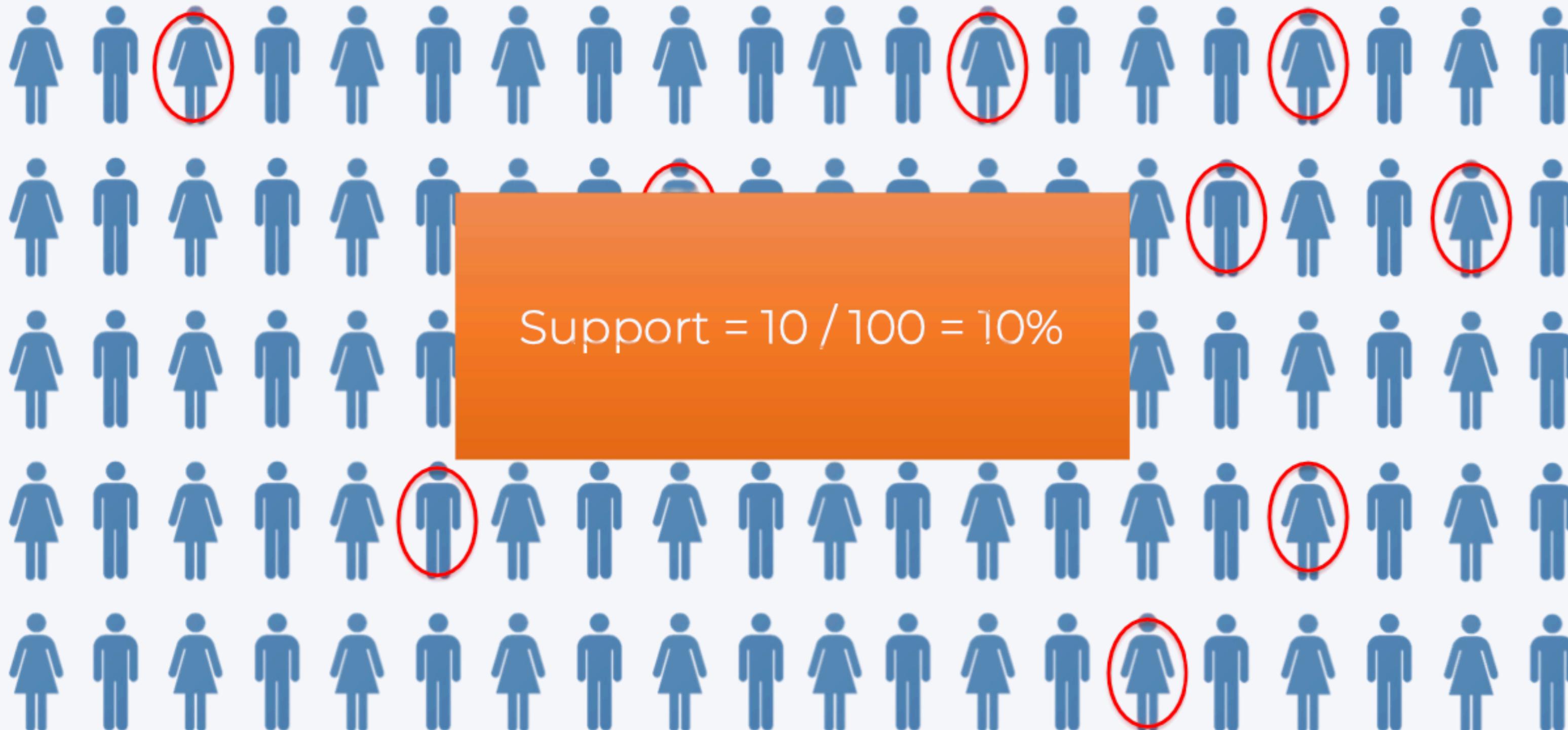
Market Basket Optimisation:

$$\text{support}(\mathbf{I}) = \frac{\# \text{ transactions containing } \mathbf{I}}{\# \text{ transactions}}$$

Support: How frequently an itemset appears in the dataset.

Additional Topics In Machine Learning

APriori - Support



Additional Topics In Machine Learning



APriori - Confidence

Movie Recommendation: $\text{confidence}(\mathcal{M}_1 \rightarrow \mathcal{M}_2) = \frac{\# \text{ user watchlists containing } \mathcal{M}_1 \text{ and } \mathcal{M}_2}{\# \text{ user watchlists containing } \mathcal{M}_1}$

Market Basket Optimisation: $\text{confidence}(\mathcal{I}_1 \rightarrow \mathcal{I}_2) = \frac{\# \text{ transactions containing } \mathcal{I}_1 \text{ and } \mathcal{I}_2}{\# \text{ transactions containing } \mathcal{I}_1}$

Confidence: The probability that a rule is correct when applied.

Additional Topics In Machine Learning

APriori - Confidence



Additional Topics In Machine Learning

APriori - Lift

Movie Recommendation:

$$\text{lift}(\mathcal{M}_1 \rightarrow \mathcal{M}_2) = \frac{\text{confidence}(\mathcal{M}_1 \rightarrow \mathcal{M}_2)}{\text{support}(\mathcal{M}_2)}$$

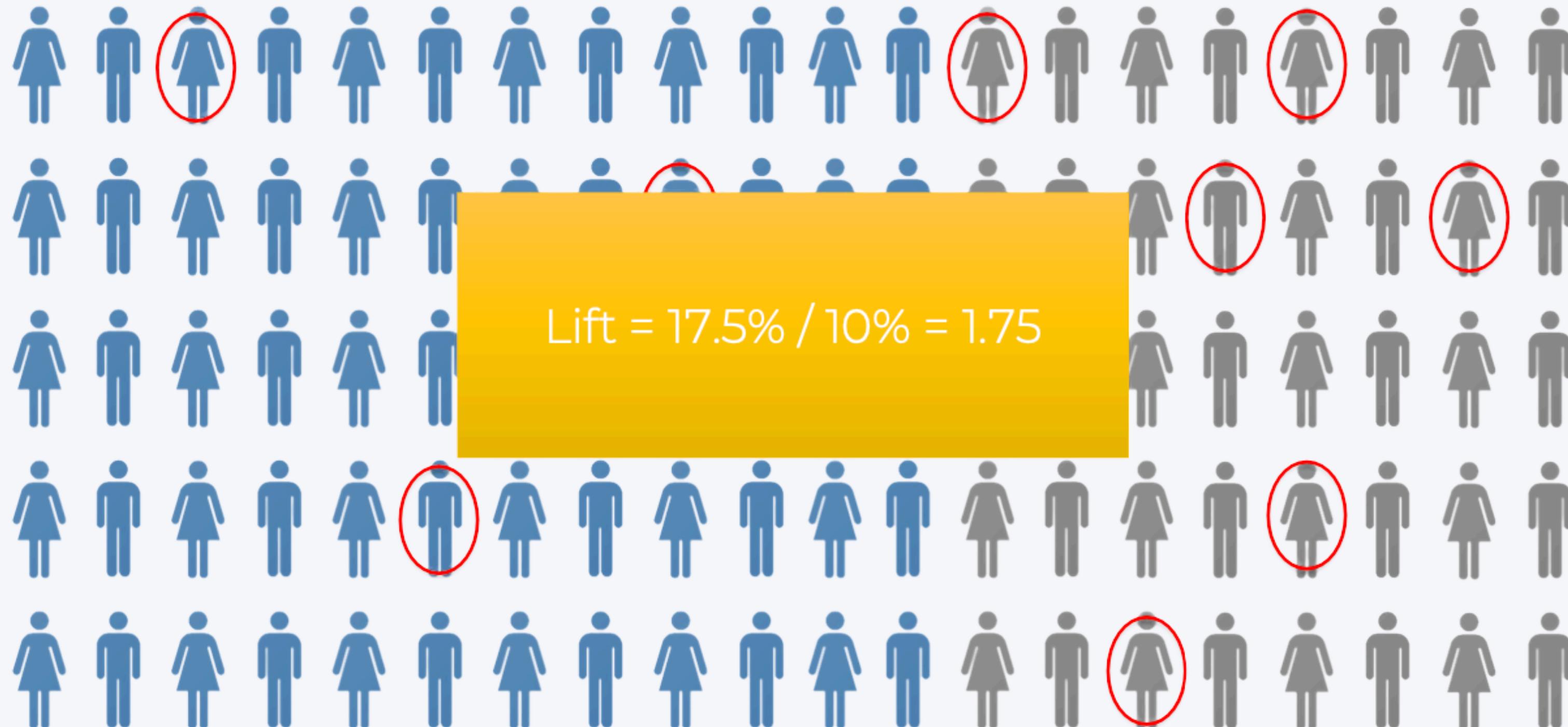
Market Basket Optimisation:

$$\text{lift}(I_1 \rightarrow I_2) = \frac{\text{confidence}(I_1 \rightarrow I_2)}{\text{support}(I_2)}$$

Lift: How much more likely items appear together than by random chance.

Additional Topics In Machine Learning

APriori - Lift



APriori - Algorithm

Step 1: Set a minimum support and confidence

Step 2: Take all the subsets in transactions having higher support than minimum support

Step 3: Take all the rules of these subsets having higher confidence than minimum confidence

Step 4: Sort the rules by decreasing lift

Additional Topics In Machine Learning

ECLAT - Support

Movie Recommendation: $\text{support}(\mathbf{M}) = \frac{\# \text{ user watchlists containing } \mathbf{M}}{\# \text{ user watchlists}}$

Market Basket Optimisation: $\text{support}(\mathbf{I}) = \frac{\# \text{ transactions containing } \mathbf{I}}{\# \text{ transactions}}$

ECLAT - Algorithm

Step 1: Set a minimum support

Step 2: Take all the subsets in transactions having higher support than minimum support

Step 3: Sort these subsets by decreasing support

Hands-On Code

Boost Sales with Python Data
Mining

Dimensionality Reduction Techniques

Principal Component Analysis (PCA)

What is PCA?

- A dimensionality reduction technique used in machine learning.
- Converts high-dimensional data into fewer principal components while preserving variance.

Key Concepts:

- Eigenvalues & Eigenvectors
- Variance Maximization
- Feature Transformation

Application:

- Image compression
- Reducing computation in ML models
- Data visualization in lower dimensions

Dimensionality Reduction Techniques

Linear Discriminant Analysis (LDA)

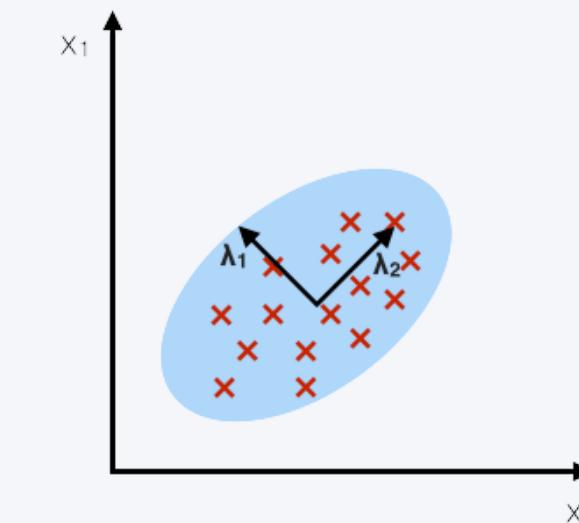
- A supervised dimensionality reduction technique used for classification.
- Unlike **PCA** (which focuses on variance), **LDA** maximizes class separability.

Applications:

- Face recognition
- Text classification
- Feature extraction

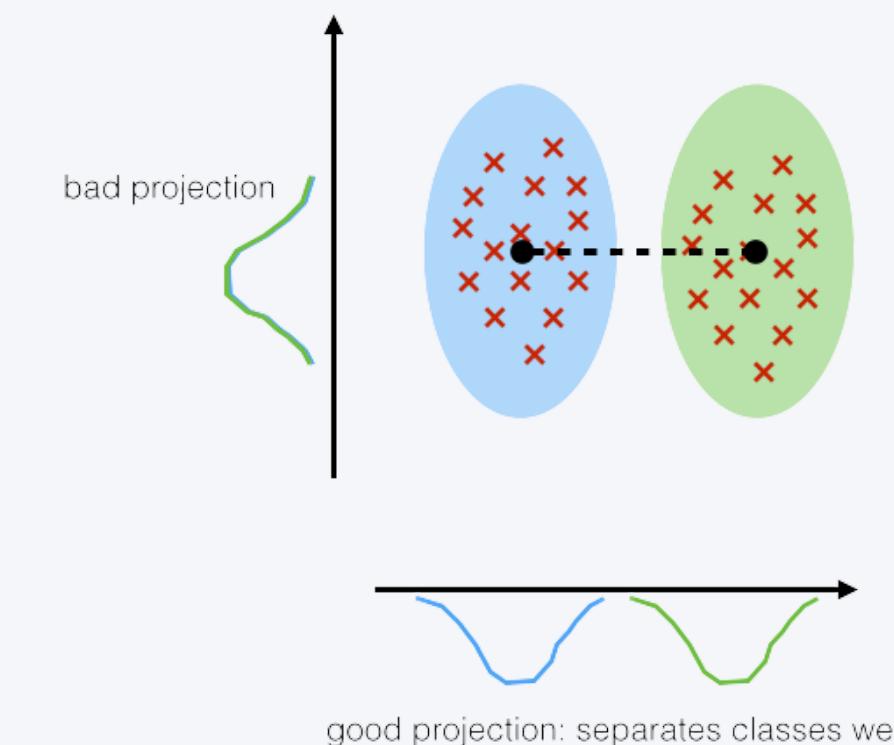
PCA:

component axes that maximize the variance



LDA:

maximizing the component axes for class-separation



Kernel PCA

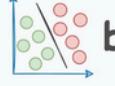
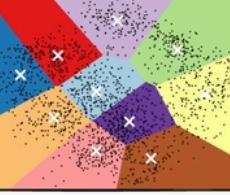
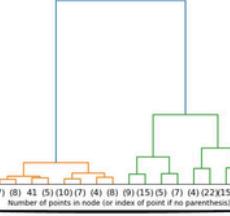
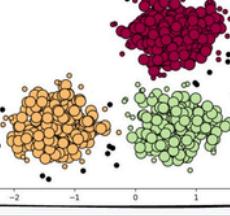
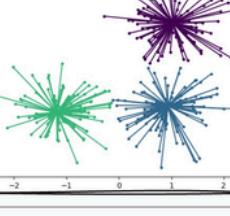
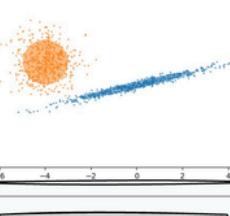
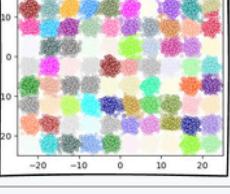
- An advanced version of PCA that can handle nonlinear data.
- Uses kernel trick to transform data into a higher-dimensional space before applying PCA.

Applications:

- Image classification
- Pattern recognition
- Nonlinear feature extraction in ML

Clustering Techniques

Clustering Techniques

6 Types of Clustering Algorithms in Machine Learning		 blog.DailyDoseofDS.com	
Clustering Algorithm Type	Clustering Methodology	Algorithm(s)	
	Centroid-based	Cluster points based on proximity to centroid	KMeans KMeans++ KMedoids
	Connectivity-based	Cluster points based on proximity between clusters	Hierarchical Clustering (Agglomerative and Divisive)
	Density-based	Cluster points based on their density instead of proximity	DBSCAN OPTICS HDBSCAN
	Graph-based	Cluster points based on graph distance	Affinity Propagation Spectral Clustering
	Distribution-based	Cluster points based on their likelihood of belonging to the same distribution.	Gaussian Mixture Models (GMMs)
	Compression-based	Transform data to a lower dimensional space and then perform clustering	BIRCH

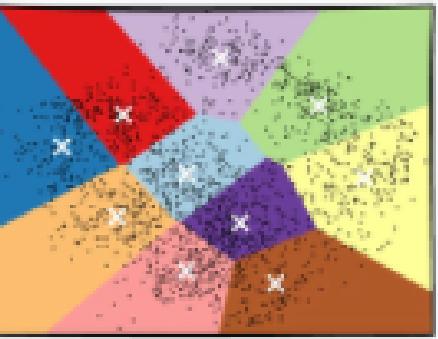
Clustering Techniques

Centroid-Based Clustering:

- **Methodology:** Groups data points around a central centroid.

Example Algorithms:

- K-Means → Most common, requires a predefined number of clusters.
- K-Means++ → Improves initialization in K-Means.
- K-Medoids → Uses actual data points as cluster centers instead of averages.

	Centroid-based	<i>Cluster points based on proximity to centroid</i>	KMeans KMeans++ KMedoids
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Clustering Techniques

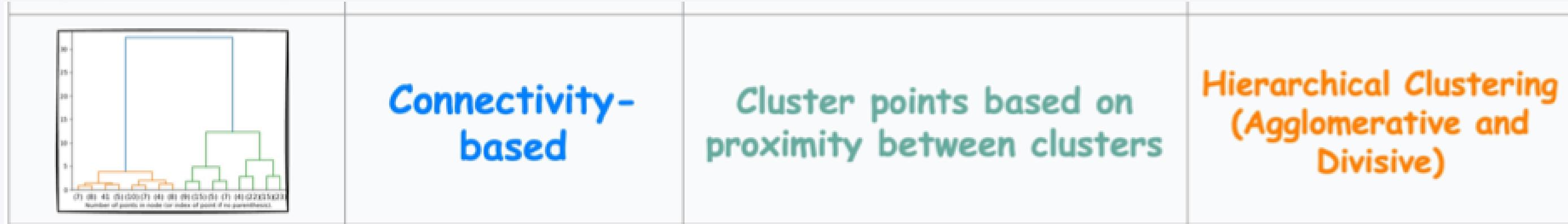
Connectivity-Based Clustering

- **Methodology:** Forms clusters based on hierarchical relationships between points.

Example Algorithms:

- Hierarchical Clustering (Agglomerative & Divisive):

- Agglomerative: Starts with individual points and merges them into clusters.
- Divisive: Starts with one large cluster and splits it into smaller ones.



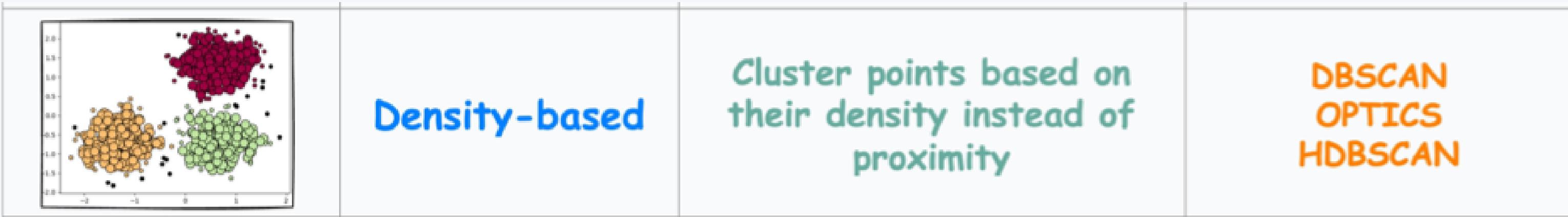
Clustering Techniques

Density-Based Clustering:

- **Methodology:** Groups data based on dense regions, allowing for irregularly shaped clusters.

Example Algorithms:

- DBSCAN → Finds dense clusters and identifies noise as outliers.
- OPTICS → Similar to DBSCAN but adjusts density thresholds dynamically.
- HDBSCAN → Hierarchical version of DBSCAN, better at handling variable density.



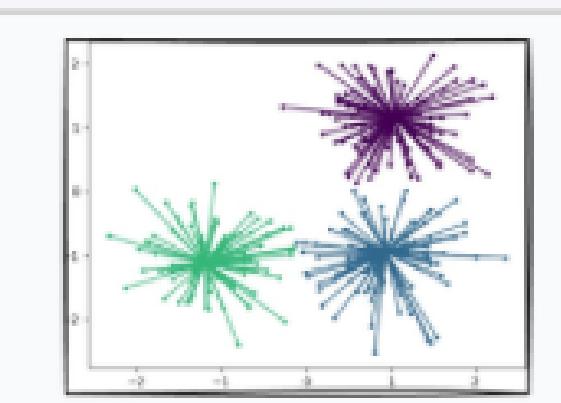
Clustering Techniques

Graph-Based Clustering

- **Methodology:** Uses graph distance (similarities between nodes) to form clusters.

Example Algorithms:

- Affinity Propagation → Message-passing algorithm that finds cluster centers.
- Spectral Clustering → Uses eigenvalues of similarity matrix for clustering.



Graph-based

Cluster points based on
graph distance

Affinity Propagation
Spectral Clustering

Clustering Techniques

Distribution-Based Clustering

- **Methodology:** Assigns probabilities to data points belonging to different distributions.

Example Algorithm:

- **Gaussian Mixture Models (GMMs)** → Uses multiple Gaussian distributions to model data.

Compression-Based Clustering

- **Methodology:** Reduces dimensionality before clustering.

Example Algorithm:

- **BIRCH (Balanced Iterative Reducing and Clustering using Hierarchies)** → Efficient for large datasets.

Clustering Techniques

Choosing the Right Clustering Algorithm

- **K-Means** → Best for well-separated, spherical clusters.
- **Hierarchical** → Good for small datasets with hierarchical relationships.
- **DBSCAN** → Works well for arbitrary-shaped clusters and noisy data.
- **GMM** → Ideal for clusters with overlapping distributions.
- **Spectral Clustering** → Best for complex structures that traditional methods struggle with.

What is Missing in This Course?

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PART -3 :Reinforcement Learning!

Reinforcement Learning is a powerful branch of Machine Learning. It is used to solve interacting problems where the data observed up **to time t** is considered to decide which action to take at **time t + 1**.

It is also used for Artificial Intelligence when **training machines to perform tasks such as walking.**

Desired outcomes provide the AI with reward, undesired with punishment. Machines learn through trial and error.

Two Important Reinforcement Learning models in ML:

1. Upper Confidence Bound (UCB)
2. Thompson Sampling

Useful Resource : [Click Here](#)

In this book you will find the theory of Reinforcement Learning and Thompson Sampling clearly explained in text, as well as many more practical activities. You will also find other AI models such as Q-Learning, Deep Learning, Deep Q-Learning, Deep Convolutional Q-Learning, and Convolutional Neural Networks.

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Congratulations