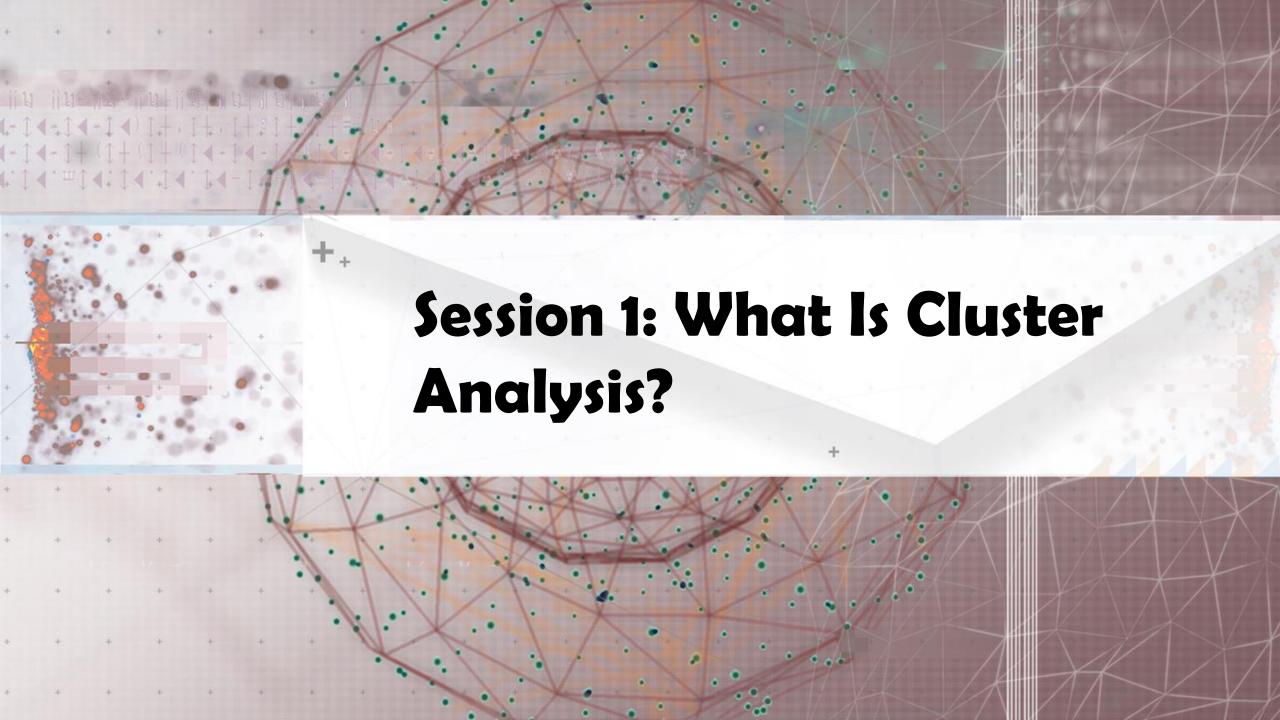


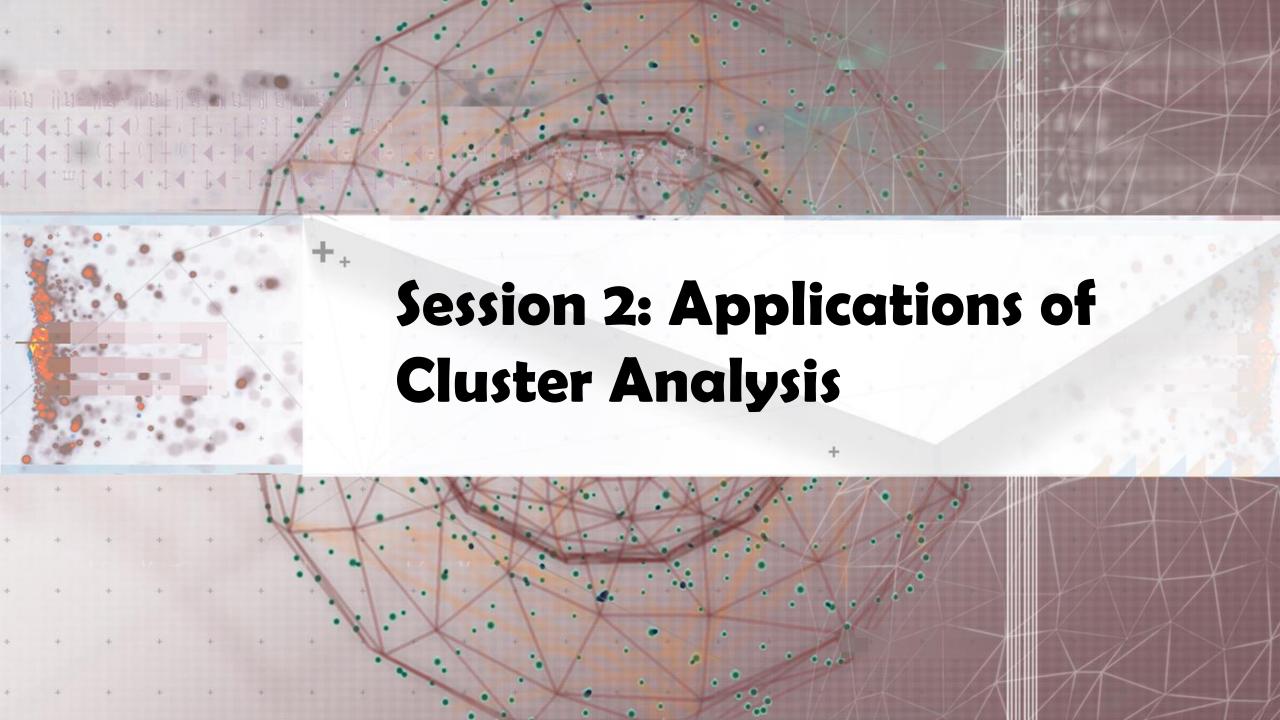
Lecture 1. Cluster Analysis: An Introduction

- What Is Cluster Analysis?
- Applications of Cluster Analysis
- Cluster Analysis: Requirements and Challenges
- Cluster Analysis: A Multi-Dimensional Categorization
- An Overview of Typical Clustering Methodologies
- An Overview of Clustering Different Types of Data
- An Overview of User Insights and Clustering
- Summary



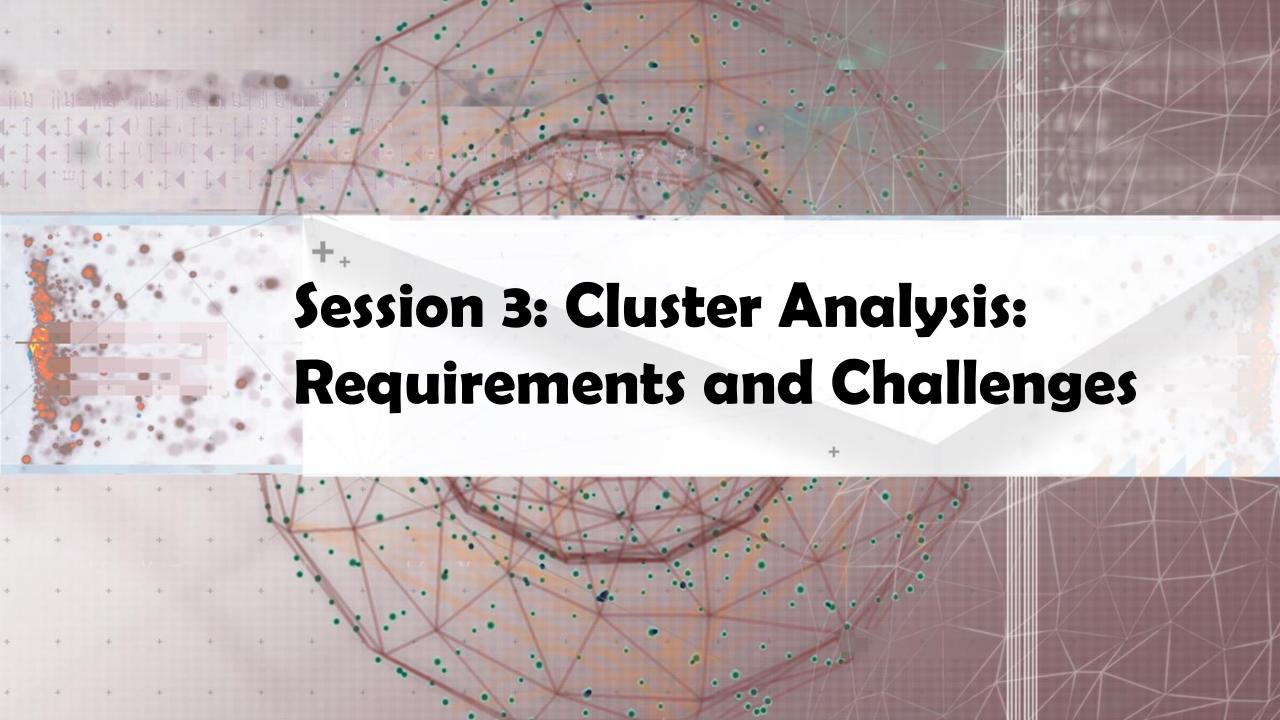
What Is Cluster Analysis?

- What is a cluster?
 - A cluster is a collection of data objects which are
 - □ Similar (or related) to one another within the same group (i.e., cluster)
 - □ Dissimilar (or unrelated) to the objects in other groups (i.e., clusters)
- □ Cluster analysis (or *clustering*, *data segmentation*, ...)
 - Given a set of data points, partition them into a set of groups (i.e., clusters) which are as similar as possible
- Cluster analysis is unsupervised learning (i.e., no predefined classes)
 - This contrasts with classification (i.e., supervised learning)
- Typical ways to use/apply cluster analysis
 - As a stand-alone tool to get insight into data distribution, or
 - As a preprocessing (or intermediate) step for other algorithms



Cluster Analysis: Applications

- ☐ A key intermediate step for other data mining tasks
 - Generating a compact summary of data for classification, pattern discovery, hypothesis generation and testing, etc.
 - Outlier detection: Outliers—those "far away" from any cluster
- □ Data summarization, compression, and reduction
 - Ex. Image processing: Vector quantization
- Collaborative filtering, recommendation systems, or customer segmentation
 - Find like-minded users or similar products
- Dynamic trend detection
 - Clustering stream data and detecting trends and patterns
- □ Multimedia data analysis, biological data analysis and social network analysis
 - Ex. Clustering images or video/audio clips, gene/protein sequences, etc.



Considerations for Cluster Analysis

Partitioning criteria

Single level vs. hierarchical partitioning (often, multi-level hierarchical partitioning is desirable)

Separation of clusters

■ Exclusive (e.g., one customer belongs to only one region) vs. non-exclusive (e.g., one document may belong to more than one class)

Similarity measure

Distance-based (e.g., Euclidean, road network, vector) vs. connectivitybased (e.g., density or contiguity)

Clustering space

□ Full space (often when low dimensional) vs. subspaces (often in high-dimensional clustering)

Requirements and Challenges

Quality

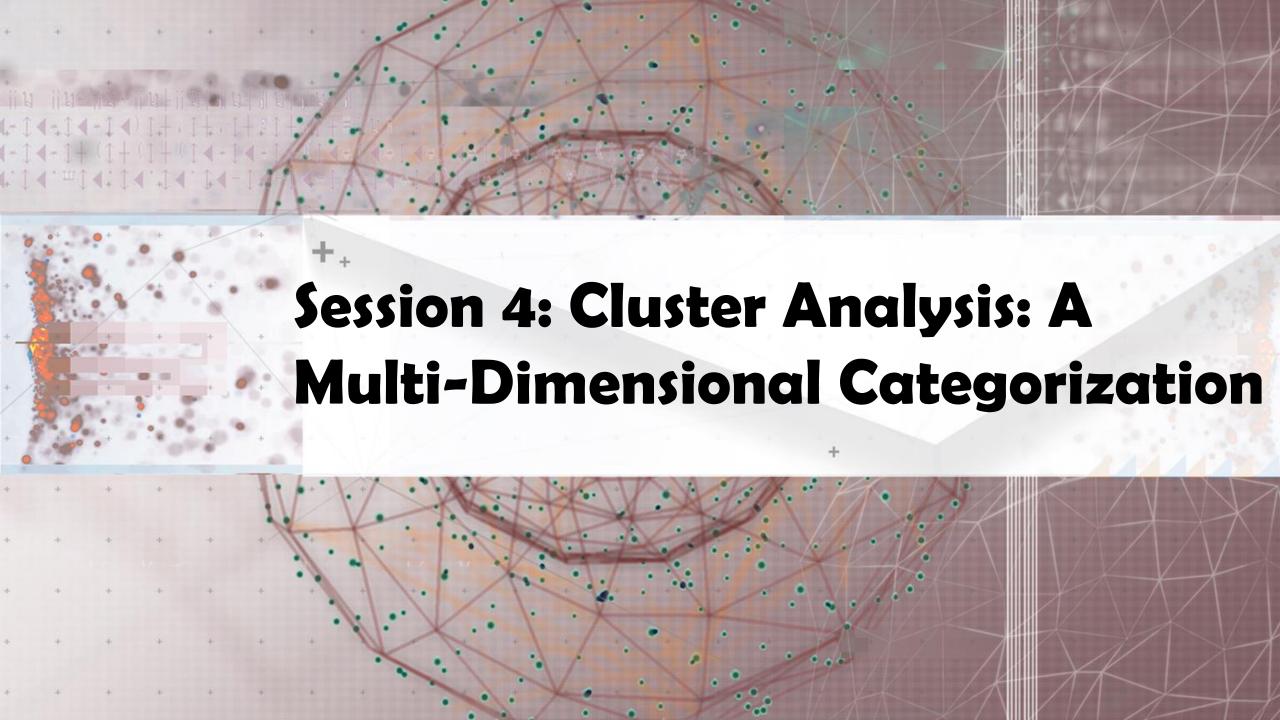
- Ability to deal with different types of attributes: Numerical, categorical, text, multimedia, networks, and mixture of multiple types
- Discovery of clusters with arbitrary shape
- Ability to deal with noisy data

Scalability

- Clustering all the data instead of only on samples
- High dimensionality
- Incremental or stream clustering and insensitivity to input order

Constraint-based clustering

- User-given preferences or constraints; domain knowledge; user queries
- Interpretability and usability



Cluster Analysis: A Multi-Dimensional Categorization

□ Technique-Centered

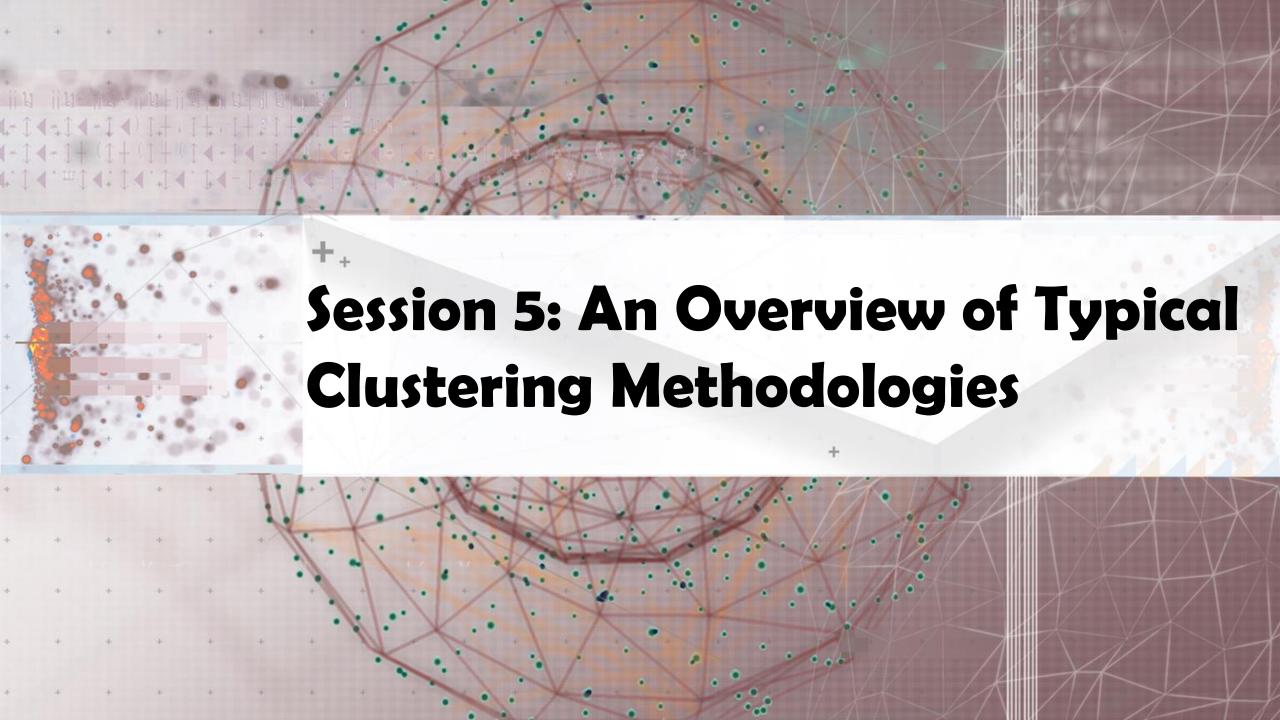
- Distance-based methods
- Density-based and grid-based methods
- Probabilistic and generative models
- Leveraging dimensionality reduction methods
- High-dimensional clustering
- Scalable techniques for cluster analysis

Data Type-Centered

 Clustering numerical data, categorical data, text data, multimedia data, timeseries data, sequences, stream data, networked data, uncertain data

Additional Insight-Centered

Visual insights, semi-supervised, ensemble-based, validation-based



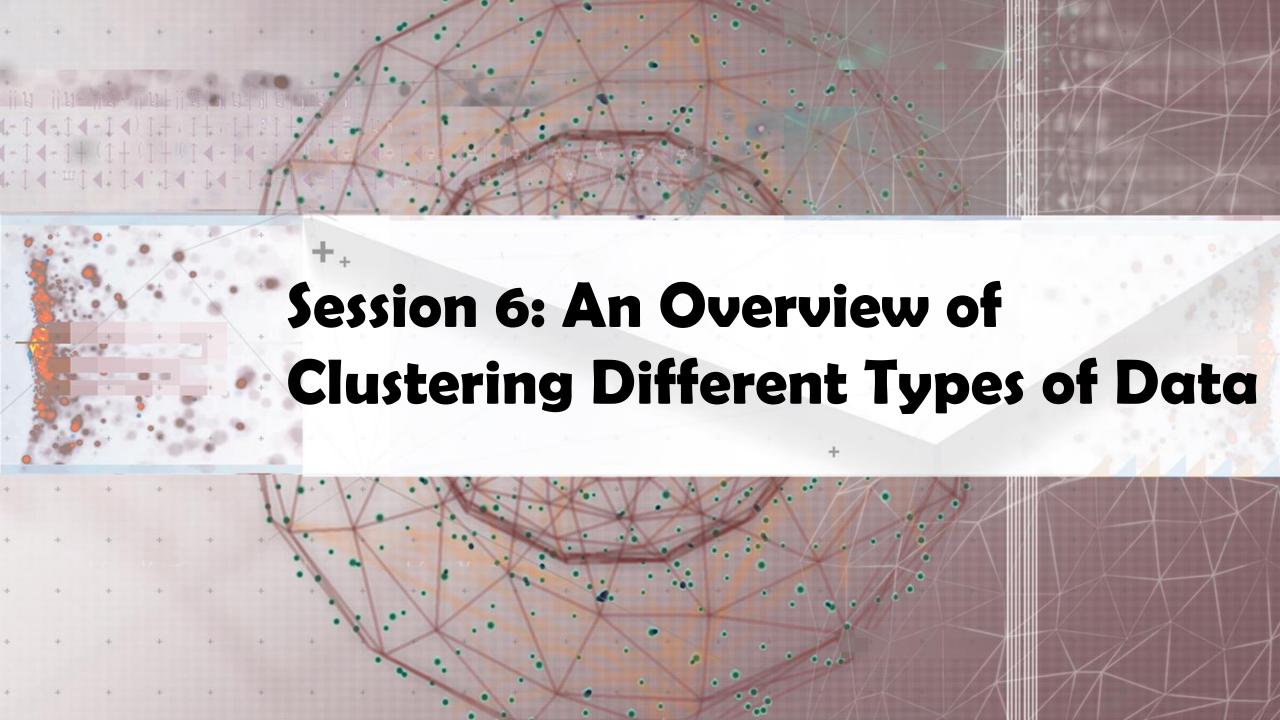
Typical Clustering Methodologies (I)

- Distance-based methods
 - □ Partitioning algorithms: K-Means, K-Medians, K-Medoids
 - ☐ Hierarchical algorithms: Agglomerative vs. divisive methods
- Density-based and grid-based methods
 - □ Density-based: Data space is explored at a high-level of granularity and then post-processing to put together dense regions into an arbitrary shape
 - ☐ Grid-based: Individual regions of the data space are formed into a grid-like structure
- □ Probabilistic and generative models: Modeling data from a generative process
 - □ Assume a specific form of the generative model (e.g., mixture of Gaussians)
 - Model parameters are estimated with the Expectation-Maximization (EM) algorithm (using the available dataset, for a maximum likelihood fit)
 - ☐ Then estimate the generative probability of the underlying data points

Typical Clustering Methodologies (II)

☐ High-dimensional clustering

- Subspace clustering: Find clusters on various subspaces
 - \square Bottom-up, top-down, correlation-based methods vs. δ -cluster methods
- □ Dimensionality reduction: A vertical form (i.e., columns) of clustering
 - Columns are clustered; may cluster rows and columns together (co-clustering)
 - ☐ Probabilistic latent semantic indexing (PLSI) then LDA: Topic modeling of text data
 - □ A cluster (i.e., topic) is associated with a set of words (i.e., dimensions) and a set of documents (i.e., rows) simultaneously
 - Nonnegative matrix factorization (NMF) (as one kind of co-clustering)
 - □ A nonnegative matrix A (e.g., word frequencies in documents) can be approximately factorized two non-negative low rank matrices U and V
 - □ Spectral clustering: Use the *spectrum* of the similarity matrix of the data to perform dimensionality reduction for clustering in fewer dimensions



Clustering Different Types of Data (I)

Numerical data

- Most earliest clustering algorithms were designed for numerical data
- □ Categorical data (including binary data)
 - □ Discrete data, no natural order (e.g., sex, race, zip-code, and market-basket)
- ☐ **Text data**: Popular in social media, Web, and social networks
 - ☐ Features: High-dimensional, sparse, value corresponding to word frequencies
 - Methods: Combination of k-means and agglomerative; topic modeling; co-clustering
- □ Multimedia data: Image, audio, video (e.g., on Flickr, YouTube)
 - Multi-modal (often combined with text data)
 - Contextual: Containing both behavioral and contextual attributes
 - □ Images: Position of a pixel represents its context, value represents its behavior
 - □ Video and music data: Temporal ordering of records represents its meaning

Clustering Different Types of Data (II)

- □ **Time-series data**: Sensor data, stock markets, temporal tracking, forecasting, etc.
 - Data are temporally dependent
 - □ Time: contextual attribute; data value: behavioral attribute
 - Correlation-based online analysis (e.g., online clustering of stock to find stock tickers)
 - □ Shape-based offline analysis (e.g., cluster ECG based on overall shapes)
- □ **Sequence data**: Weblogs, biological sequences, system command sequences
 - Contextual attribute: Placement (rather than time)
 - □ Similarity functions: Hamming distance, edit distance, longest common subsequence
 - □ Sequence clustering: Suffix tree; generative model (e.g., Hidden Markov Model)
- Stream data:
 - Real-time, evolution and concept drift, single pass algorithm
 - □ Create efficient intermediate representation, e.g., micro-clustering

Clustering Different Types of Data (III)

□ Graphs and homogeneous networks

- Every kind of data can be represented as a graph with similarity values as edges
- Methods: Generative models; combinatorial algorithms (graph cuts); spectral methods; non-negative matrix factorization methods

Heterogeneous networks

- □ A network consists of multiple typed nodes and edges (e.g., bibliographical data)
- Clustering different typed nodes/links together (e.g., NetClus)
- ☐ Uncertain data: Noise, approximate values, multiple possible values
 - Incorporation of probabilistic information will improve the quality of clustering
- □ **Big data**: Model systems may store and process very big data (e.g., weblogs)
 - Ex. Google's MapReduce framework
 - ☐ Use *Map* function to distribute the computation across different machines
 - ☐ Use Reduce function to aggregate results obtained from the Map step



User Insights and Interactions in Clustering

- □ Visual insights: One picture is worth a thousand words
 - Human eyes: High-speed processor linking with a rich knowledge-base
 - ☐ A human can provide intuitive insights; HD-eye: visualizing HD clusters
- □ **Semi-supervised insights**: Passing user's insights or intention to system
 - User-seeding: A user provides a number of labeled examples, approximately representing categories of interest
- Multi-view and ensemble-based insights
 - Multi-view clustering: Multiple clusterings represent different perspectives
 - Multiple clustering results can be ensembled to provide a more robust solution
- □ Validation-based insights: Evaluation of the quality of clusters generated
 - May use case studies, specific measures, or pre-existing labels



Summary: Cluster Analysis—An Introduction

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Recommended Readings

- Major Reference Books on Cluster Analysis
 - Jiawei Han, Micheline Kamber, and Jian Pei. Data Mining: Concepts and Techniques. Morgan Kaufmann, 3rd ed., 2011 (Chapters 10 & 11)
 - □ Charu Aggarwal and Chandran K. Reddy (eds.). Data Clustering: Algorithms and Applications. CRC Press, 2014
 - Mohammed J. Zaki and Wagner Meira, Jr.. Data Mining and Analysis: Fundamental Concepts and Algorithms. Cambridge University Press, 2014
- ☐ Reference paper for this lecture
 - □ Charu Aggarwal. An Introduction to Clustering Analysis. *in* Aggarwal and Reddy (eds.). Data Clustering: Algorithms and Applications (Chapter 1). CRC Press, 2014