Cluster Analysis in Data Mining: Course Overview

What Is Cluster Analysis?

- When flying over a city, one can easily identify fields, forests, commercial areas, and residential areas based on their features, without anyone's explicit "training" - this is the power of cluster analysis. This course will systematically study cluster analysis methods and help answer the following:
  - What are the different proximity measures for effective clustering?
  - Can we cluster a massive number of data points efficiently?
  - Can we find clusters of arbitrary shape? At multiple levels of granularity?
  - How can we judge the quality of the clusters discovered by our system?

The Value of Cluster Analysis

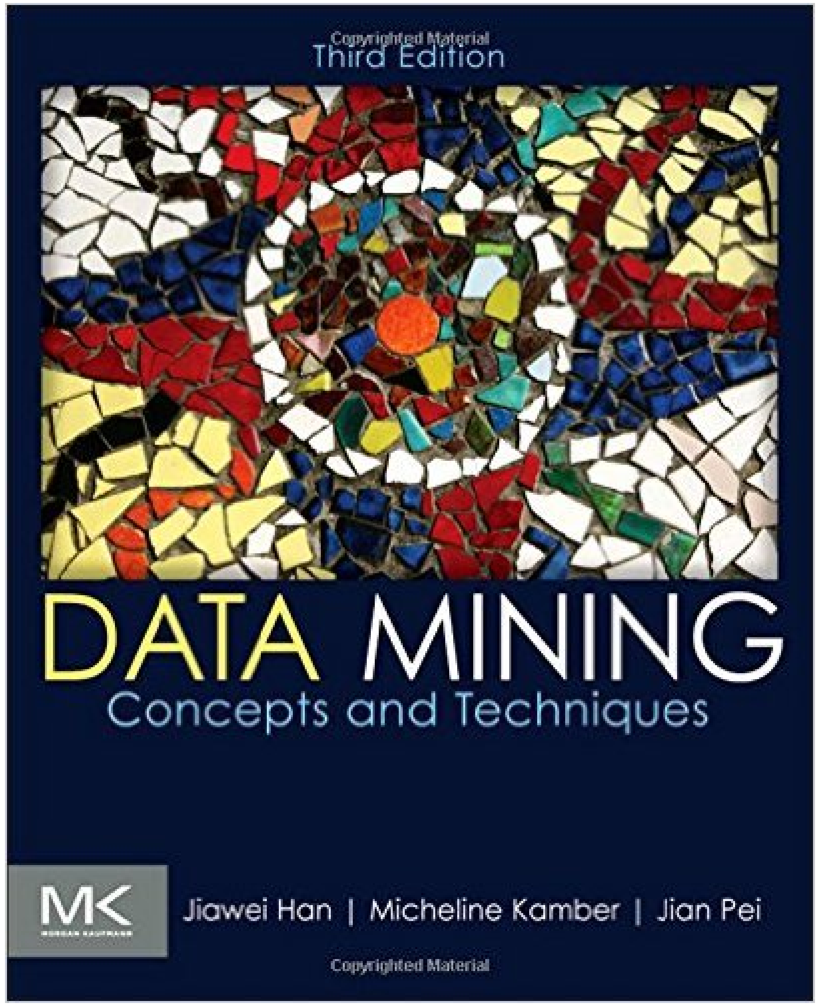
- What is the value of cluster analysis?
  - Cluster analysis helps you partition massive data into groups based on its features.
  - Cluster analysis will often help subsequent data mining processes such as pattern discovery, classification, and outlier analysis
- What roles does cluster analysis play in the Data Mining Specialization?
  - You will learn various scalable methods to find clusters from massive data.
  - You will learn how to mine different kinds of clusters effectively.
  - You will also learn how to evaluate the quality of the clusters you find.
  - Cluster analysis will help with classification, outlier analysis, and other data mining tasks.

Broad Applications of Cluster Analysis

- Data summarization, compression, and reduction
  - Examples: Image processing or vector quantization
- Collaborative filtering, recommendation systems, or customer segmentation
  - Finding 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
  - Example: Clustering images or video/audio clips, gene/protein sequences, etc.
- A key intermediate step for other data mining tasks
  - Generating a compact summary of data for classification, pattern discovery, and hypothesis generation and testing
  - Outlier detection: Outliers - those “far away” from any cluster

Major Reference Readings for the Course

- **Textbook**
  - Han, J., Kamber, M., & Pei, J. (2011). *Data mining: Concepts and techniques (3rd ed.)*. Morgan Kaufmann.
  - **Chapters most related to the course**
    - Chapter 2: Getting to Know Your Data (Section 2.4: Measuring Data Similarity and Dissimilarity)
    - Chapter 10: Cluster Analysis: Basic Concepts and Methods



- Other references will be listed at the end of each lecture video.

What Is Cluster Analysis?

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

Applications of Cluster Analysis

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.

Requirements and Challenges

Considerations for Cluster Analysis

- **Partitioning criteria**
  - Single level vs. hierarchical partitioning (often, multi-level hierarchical partitioning is desirable, e.g., grouping topical terms)
- **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. connectivity-based (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**

A Multi-Dimensional Categorization

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, time-series data, sequences, stream data, networked data, uncertain data
- **Additional Insight-Centered**
  - Visual insights, semi-supervised, ensemble-based, validation-based

An Overview of Typical Clustering Methodologies

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
    - 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

An Overview of Clustering Different Types of Data

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 R*educe* function to aggregate results obtained from the Map step

An Overview of User Insights and Clustering

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

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