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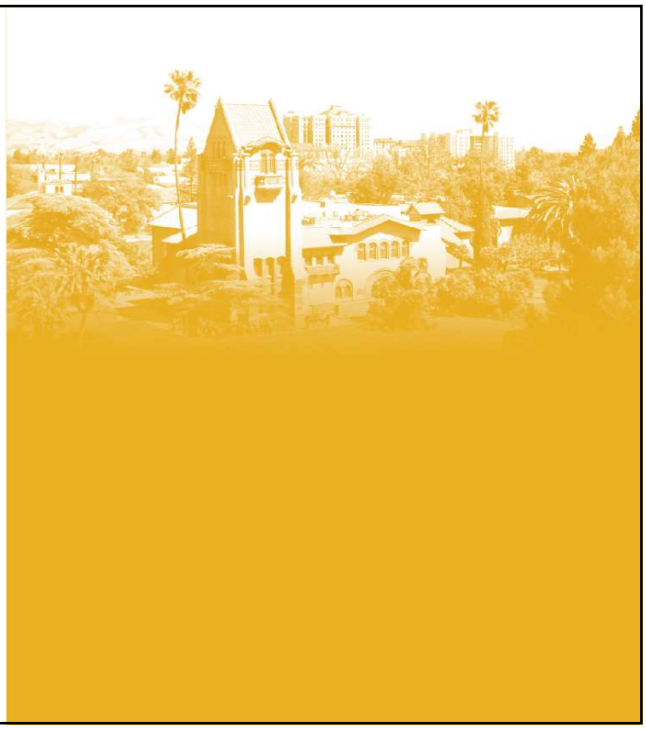
Introduction to Data Mining



1

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Agenda

- Why Data Mining?
- What Is Data Mining?
- A Multi-Dimensional View of Data Mining
- What Kinds of Data Can Be Mined?
- What Kinds of Patterns Can Be Mined?
- What Kinds of Technologies Are Used?
- What Kinds of Applications Are Targeted?
- Summary

2

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Why Data Mining?

- The Explosive Growth of Data: from terabytes to petabytes
  - Data collection and data availability
    - Automated data collection tools, database systems, Web, computerized society
  - Major sources of abundant data
    - Business: Web, e-commerce, transactions, stocks, …
    - Science: Remote sensing, bioinformatics, scientific simulation, …
    - Society and everyone: news, digital cameras, YouTube
- We are drowning in data, but starving for knowledge!

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What Is Data Mining?

- Data mining (knowledge discovery from data)
  - Extraction of interesting (non-trivial, implicit, previously unknown and potentially useful) patterns or knowledge from huge amount of data
  - Data mining: a misnomer?
- Alternative names
  - Knowledge Discovery (mining) in Databases (KDD), knowledge extraction, data/pattern analysis, data archeology, data dredging, information harvesting, business intelligence, etc.
- Not everything is "data mining"…
  - Simple search and query processing
  - (Deductive) Expert systems

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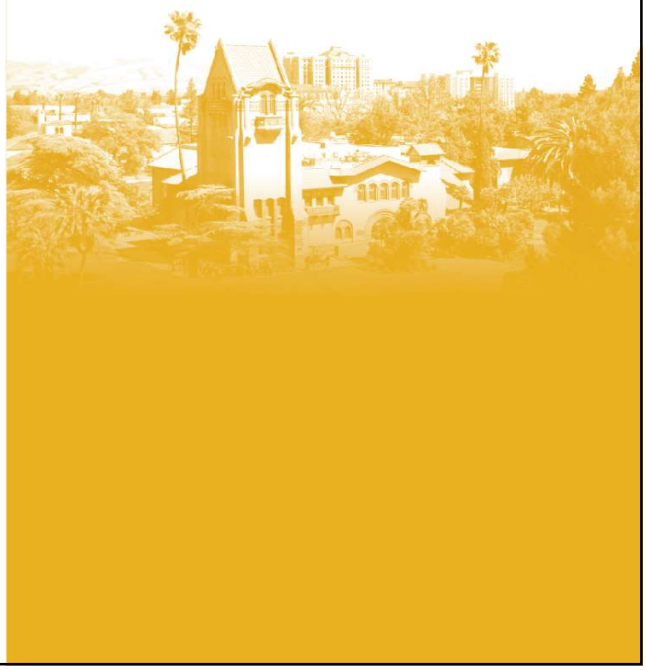
Recall from DATA270…



5

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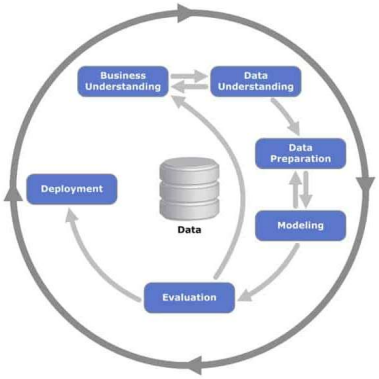
CRISP-DM Methodology

- CRISP-DM: CRoss Industry Standard Process for Data Mining.
- A standard on data mining/data science process published in 1999.
- Six phases that naturally describes the data science life cycle.
- Usually implemented with other PM approaches.



https://www.datascience-pm.com/crisp-dm-2/

6

6

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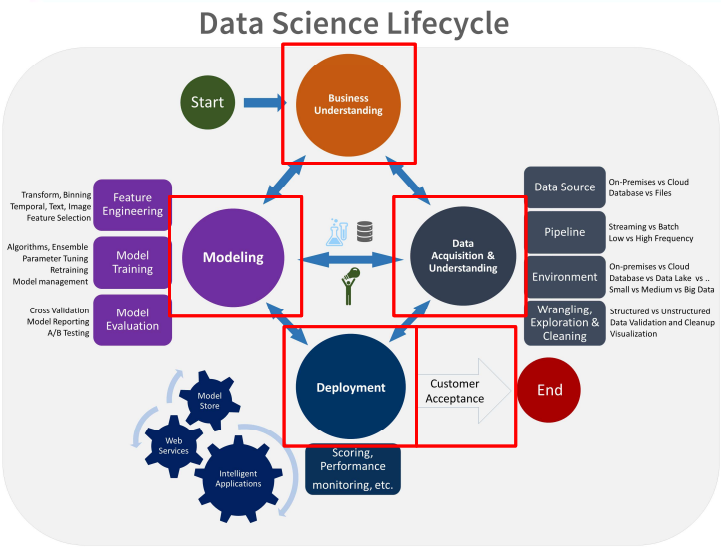
Team Data Science Process (TDSP)



https://docs.microsoft.com/en-us/azure/architecture/data-science-process/lifecycle-data

7

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Data Process

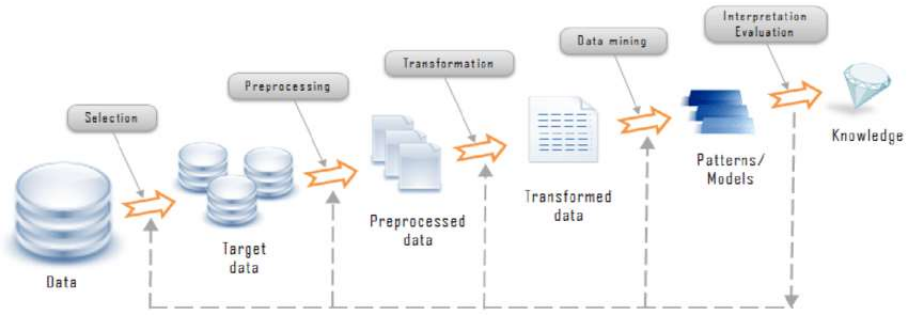

Image adopted from internet srouce

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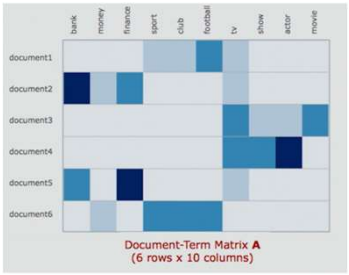
Record or Tabular Dataset

Sale ID	Time	Customer	Product ID	Quantity
S00001	12/1/2012 9:00:00 AM	C0001	P025	1
S00002	12/1/2012 9:05:58 AM	C0025	P025	3
S00003	12/1/2012 9:11:33 AM	C0010	P001	2
S00004	12/1/2012 9:17:16 AM	C0017	P023	4
S00005	12/1/2012 9:23:04 AM	C0018	P016	5
S00006	12/1/2012 9:28:43 AM	C0011	P018	4
S0007	12/1/2012 9:34:07 AM	C0015	P005	1

Record or Transaction Data



Document-Term Matrix

	Variables			
Cases	sepal length	sepal width	petal length	petal width	class
	5.1	3.5	1.4	0.2	Iris-setosa
	4.9	3	1.4	0.2	Iris-setosa
	6.5	3.2	5.1	2	Iris-virginica
	6.4	2.7	5.3	1.9	Iris-virginica
	6.8	3	5.5	2.1	Iris-virginica
	6.7	3.1	4.4	1.4	Iris-versicolor
	5.6	3	4.5	1.5	Iris-versicolor
	5.8	2.7	4.1	1	Iris-versicolor

Data Matrix

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 9 & 0 \\ 0 & 8 & 0 & 0 & 0 & 0 \\ 4 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 5 \\ 0 & 0 & 2 & 0 & 0 & 0 \end{bmatrix}$$

Rows	Columns	Values
5	6	6
0	4	9
1	1	8
2	0	4
2	3	2
3	5	5
4	2	2

Sparse Data Matrix

Images adopted from various internet pages

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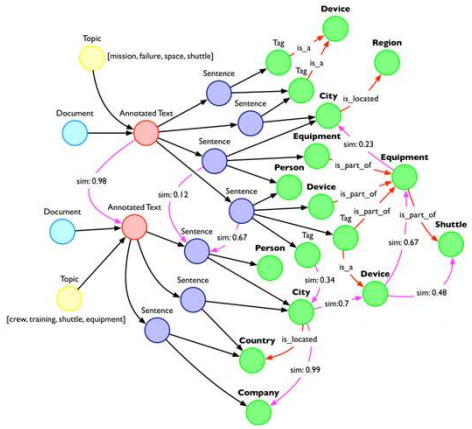
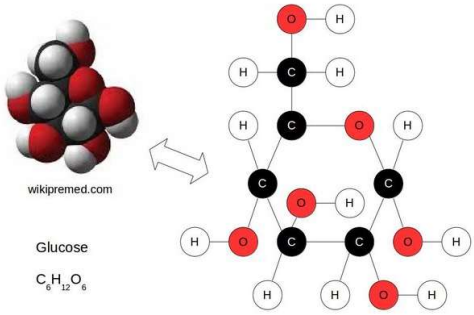
Graph-Based Dataset



Data with Relationships among Objects



Data with Objects that are Graphs

Images adopted from various sources.

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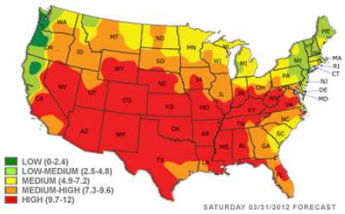
Ordered Dataset

Time	Customer	Items Purchased
t1	C1	A, B
t2	C3	A, C
t2	C1	C, D
t3	C2	A, D
t4	C2	E
t5	C1	A, E

Customer	Time and Items Purchased
C1	(t1: A,B) (t2:C,D) (t5:A,E)
C2	(t3: A, D) (t4: E)
C3	(t2: A, C)

Sequential Data

Time Series Data



Spatial Data

Sequence Data

Images adopted from various sources.

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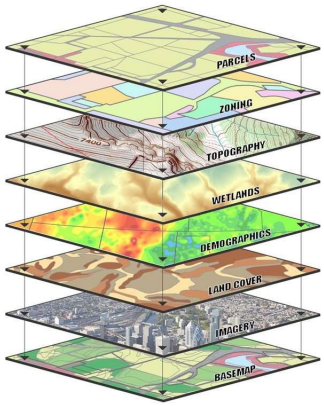
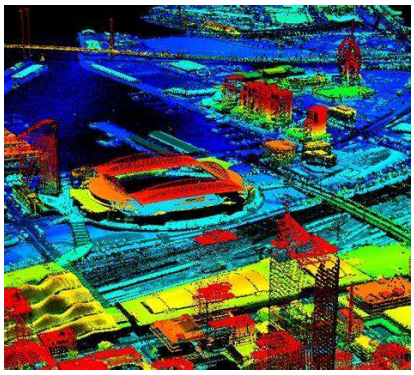
Other Ordered Dataset



GIS Data



LiDAR Data

Satellite Data

Images adopted from various sources.

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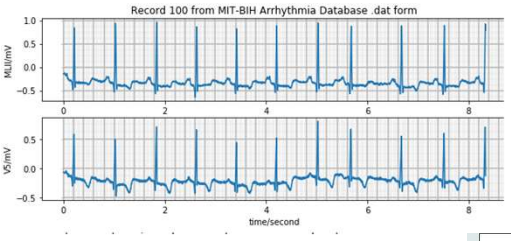
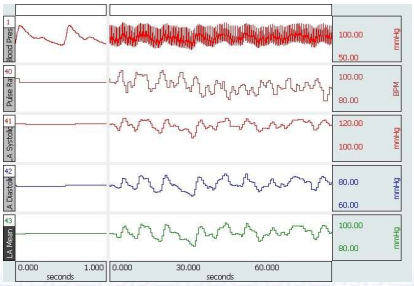
More Ordered Dataset



ECG Data



Blood Pressure Data

Wellness Data

Images adopted from various sources.

13

13

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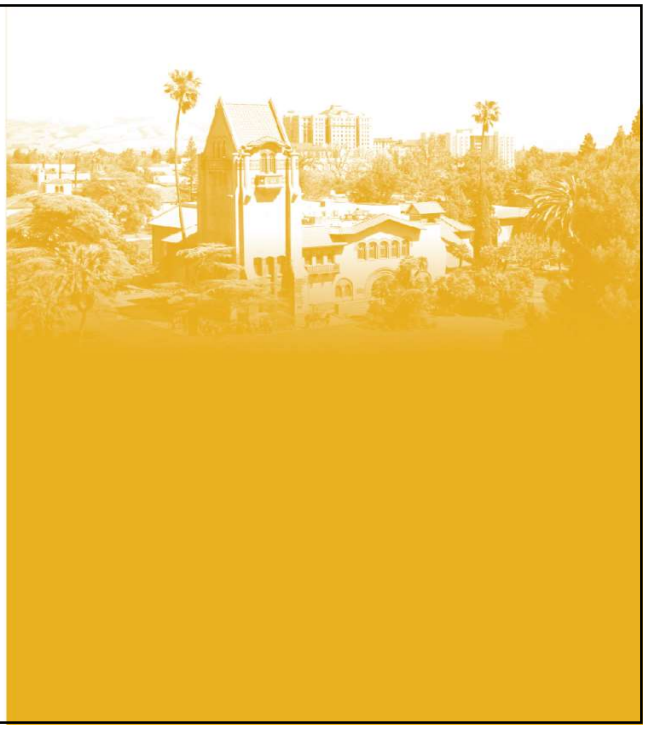
Back to DATA240…



14

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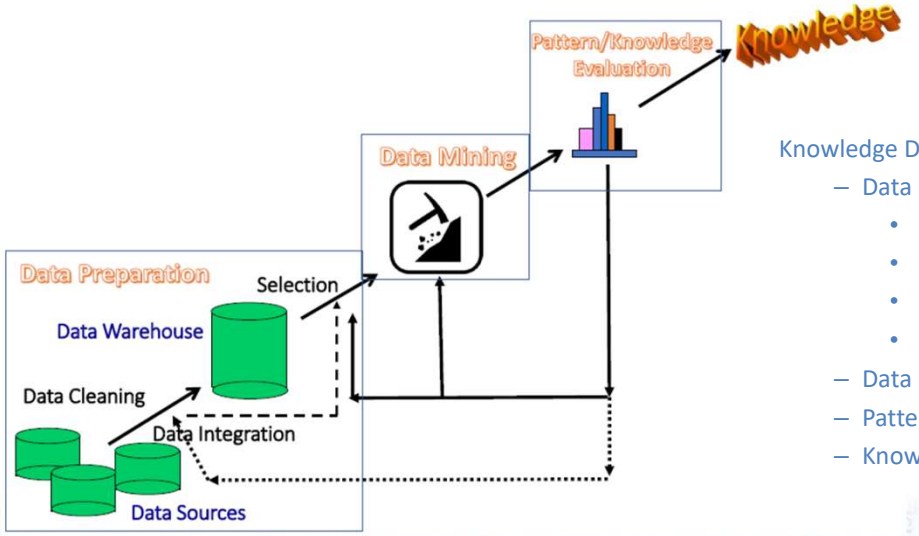
Data Mining: An Essential Step in Traditional Knowledge Discovery



Knowledge Discovery Process
- Data preparation
  - Data cleaning
  - Data integration
  - Data transformation
  - Data selection
- Data mining
- Pattern/model evaluation
- Knowledge presentation

15

15

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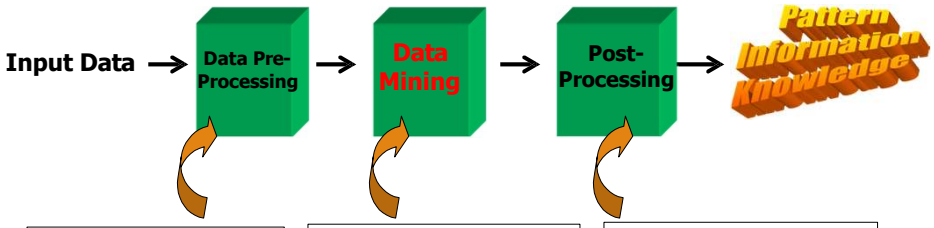
KDD Process: A View from Machine Learning



Data Integration	Pattern Discovery	Pattern Evaluation
Normalization	Classification	Pattern Selection
Feature Selection	Clustering	Pattern Interpretation
Dimension Reduction	Outlier Analysis	Pattern Visualization
	… … … …	

16

16

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Data Mining vs. Data Exploration

Which view do you prefer?

- KDD vs. ML vs. BI

Data Mining vs. Data Exploration

- Business Intelligence view
  - Warehouse, data cube, reporting but not much mining
- Business Objects vs. Data Mining Tools
- Supply chain example: mining vs. OLAP vs. presentation tools
- Data Presentation vs. Data Exploration

17

17

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Multi-Dimensional View of Data Mining

- Data to be mined
  - Database data, data warehouse, transactional data, stream, spatiotemporal, time-series, sequence, text and web, multi-media, graphs & social and information networks
- Knowledge to be mined or Data Mining Functions
  - Characterization, discrimination, association, classification, clustering, outlier analysis, …
  - Descriptive vs. predictive data mining
  - Multiple/integrated functions and mining at multiple levels
- Techniques utilized
  - Data-intensive, data warehouse (OLAP), machine learning, statistics, pattern recognition, visualization, high-performance, etc.
- Applications adapted
  - Retail, telecommunication, banking, fraud analysis, bio-data mining, stock market analysis, text mining, Web mining, etc.

18

18

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Diversity of Data Types for Data Mining

- Structured: uniform, record- or table-like structures, defined by data dictionaries, with a fixed set of attributes, each with a fixed set of value ranges and semantic meaning
  - e.g. data stored in relational databases, data cubes, data matrices, and many data warehouses
- Semi-structured: allow a data object to contain a set value, a small set of heterogeneous typed values, or nested structures, or to allow the structure of objects or sub-objects to be defined flexibly and dynamically
- Data having certain structures with clearly defined semantic meaning, such as transactional data set, sequence data set (e.g., time-series data, gene or protein data, or Weblog data)
  - Graph or network data: A more sophisticated type of semi-structured data set
  - Unstructured data: text data and multimedia (e.g., audio, image, video) data

The real-world data can often be a mixture of structured, semi-structured & unstructured data

19

19

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Diversity of Data Types for Data Mining

- Different applications with different data sets and require different data analysis methods
  - Sequence data: Biological sequences vs. shopping transaction sequences
  - Time-series: ordered set of numerical values with equal time interval
  - Spatial, temporal and spatiotemporal data
  - Graph and network data: Social networks, computer communication networks, biological networks, and information networks may carry rather different semantics
- On the same data set, finding different kinds of patterns: require different mining methods
  - e.g. software programs: finding plagiarized modules vs. finding copy-and-paste bugs
- Stored vs. Streaming data
  - Stored data: Finite, stored in various kinds of large data repositories
  - Streaming data (e.g., video surveillance or remote sensing): Dynamic, constantly coming, infinite, real-time response—posing challenges on effective data mining

20

20

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Mining Various Kinds of Knowledge

- Multidimensional Data Summarization
- Mining Frequent Patterns, Associations, and Correlations
- Classification and Regression for Predictive Analysis
- Cluster Analysis
- Deep Learning
- Outlier Analysis

Are All Mining Results Interesting?

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Multidimensional Data Summarization

- Information integration and data warehouse construction
  - Data cleaning, transformation, integration, and multidimensional data model
- Data Cube technology
  - Scalable methods for computing (i.e., materializing) multidimensional aggregates
  - OLAP (online analytical processing)
- Multidimensional concept description: Characterization and discrimination
  - Generalize, summarize, and contrast data characteristics, e.g., dry vs. wet region

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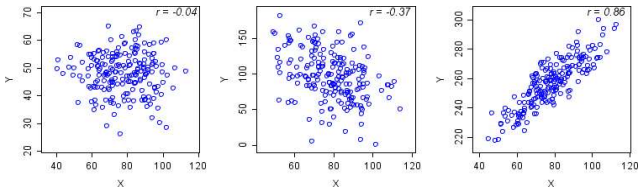
Pattern Discovery: Mining Frequent Patterns, Associations, & Correlations

- Frequent patterns:
  - What items are frequently purchased together in your Walmart?
- Association and Correlation Analysis



- A typical association rule
  - Diaper ➔ Beer [0.5%, 75%] (support, confidence)
  - Are strongly associated items also strongly correlated?
- How to mine such patterns and rules efficiently in large datasets?
- How to use such patterns for classification, clustering, and other applications?

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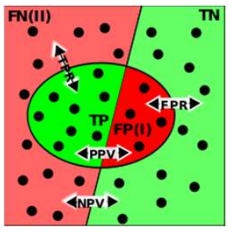
Classification and Regression for Predictive Analysis

- Classification and Label Prediction
  - Construct models (functions) based on some training examples
  - Describe and distinguish classes or concepts for future prediction
    - e.g. Classify countries based on (climate)
    - e.g. Classify cars based on (gas mileage)
  - Predict some unknown class labels



- Typical Methods
  - Decision trees, naïve Bayesian classification, support vector machines, neural networks, rule-based classification, pattern-based classification, logistic regression, …
- Typical Applications
  - Credit card fraud detection, direct marketing, classifying stars, diseases, web-pages, …

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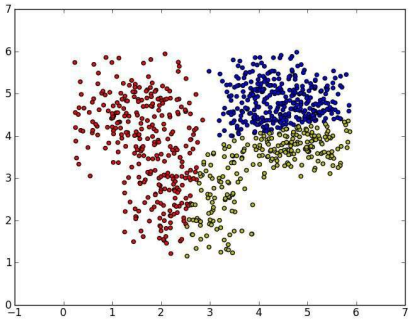
Cluster Analysis

- Unsupervised Learning (i.e., Class label is unknown)
- Group data to form new categories (i.e., clusters)
  e.g. cluster houses to find distribution patterns
- Principle
  - Maximizing intra-class similarity & minimizing interclass similarity
- Many methods and applications…



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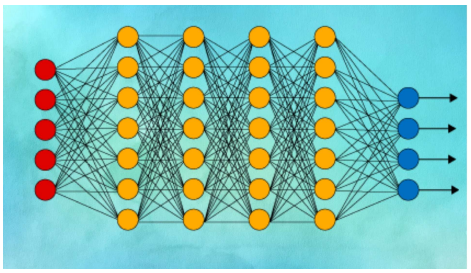
Deep Learning

- Various neural network architectures are available:
  - Feed-forward neural networks
  - Convolutional neural networks
  - Recurrent neural networks
  - Graph neural networks
  - Transformer



- Broad applications in computer vision, natural language processing, machine translation, social network analysis, and so on
- Reshaping a variety of data mining tasks:
  e.g. classification, clustering, outlier detection, and reinforcement learning

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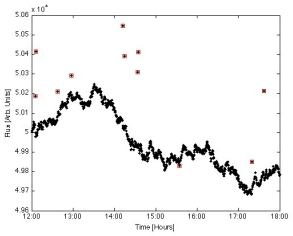
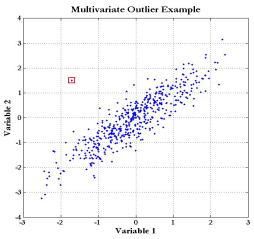
Outlier Analysis

- Outlier: A data object that does not comply with the general behavior of the data
- Noise or exception?—One person's garbage could be another person's treasure
- Methods: by product of clustering or regression analysis, …
- Useful in fraud detection, rare events analysis





27

27

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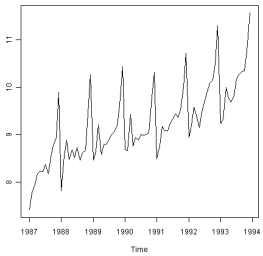
Time and Ordering: Sequential Pattern, Trend and Evolution Analysis

- Sequence, trend and evolution analysis
  - Trend, time-series, and deviation analysis
    - e.g., regression and value prediction
  - Sequential pattern mining
    - e.g., buy digital camera, then buy large memory cards
  - Periodicity analysis
  - Motifs and biological sequence analysis
    - Approximate and consecutive motifs
  - Similarity-based analysis
- Mining data streams
  - Ordered, time-varying, potentially infinite, data streams



28

28

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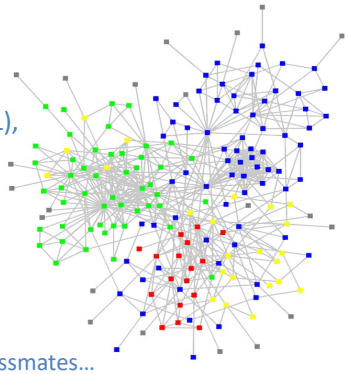
Structure and Network Analysis



- Graph mining
  - Finding frequent subgraphs (e.g., chemical compounds), trees (XML), substructures (web fragments)
- Information network analysis
  - Social networks: actors (objects, nodes) and relationships (edges)
    - e.g. author networks in CS, terrorist networks
  - Multiple heterogeneous networks
    - e.g. A person could be multiple information networks: friends, family, classmates…
- Web mining
  - Web is a big information network: from PageRank to Google
  - Analysis of Web information networks
    - Web community discovery, opinion mining, usage mining, …

29

29

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Evaluation of Knowledge

- Are all mined knowledge interesting?
  - One can mine tremendous amount of "patterns"
  - Some may fit only certain dimension space (time, location, …)
  - Some may not be representative, may be transient, …
- Evaluation of mined knowledge ➔ directly mining only interesting knowledge?
  - Descriptive vs Predictive
  - Coverage
  - Accuracy
  - Timeliness

30

30

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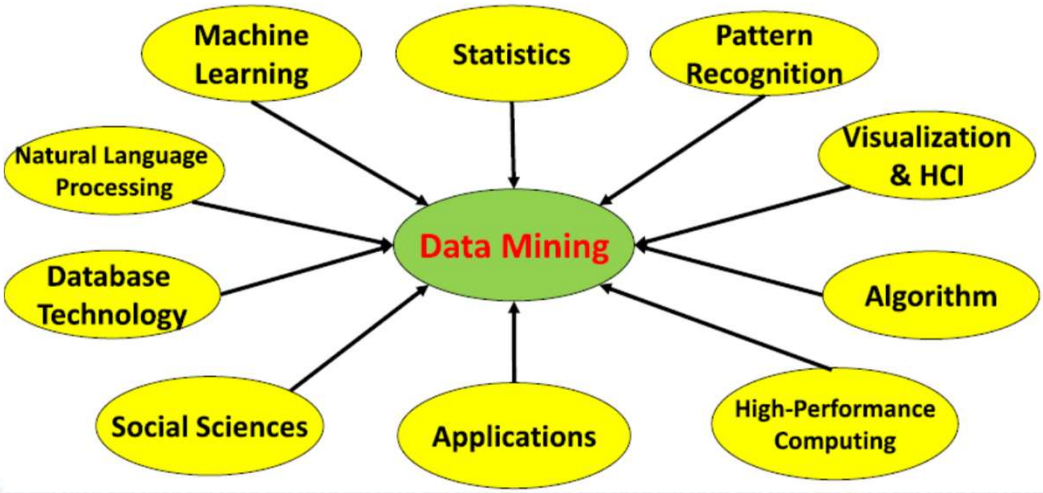
Data Mining: Confluence of Multiple Disciplines



31

31

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Why Confluence of Multiple Disciplines?

- Tremendous amount of data
  - Algorithms must be scalable to handle big data
- High-dimensionality of data
  - Micro-array may have tens of thousands of dimensions
- High complexity of data
  - Data streams and sensor data
  - Time-series data, temporal data, sequence data
  - Structure data, graphs, social and information networks
  - Spatial, spatiotemporal, multimedia, text and Web data
  - Software programs, scientific simulations
- New and sophisticated applications

32

32

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Applications of Data Mining

- Web page analysis: classification, clustering, ranking
- Collaborative analysis & recommender systems
- Basket data analysis to targeted marketing
- Biological and medical data analysis
- Data mining and software engineering
- Data mining and text analysis
- Data mining and social and information network analysis
- Built-in (invisible data mining) functions in Google, MS, Yahoo!, Linked, Facebook, …
- Major dedicated data mining systems/tools
  - SAS, MS SQL-Server Analysis Manager, Oracle Data Mining Tools)

33

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Summary

- Data mining: Discovering interesting patterns & knowledge from massive amounts of data.
- Traditional KDD process includes data cleaning, data integration, data selection, transformation, data mining, pattern evaluation, and knowledge presentation
- Different data mining method on a wide variety of data.
- Data Mining functionalities: summarization, pattern discovery, classification, clustering, deep learning, outlier analysis, trend and outlier analysis, …
- Data Mining is a confluence of multiple disciplines
- Data Mining has broad applications

34