# DATA MINING AND DATA WAREHOUSING
# IT 3031

# Chapter Contents

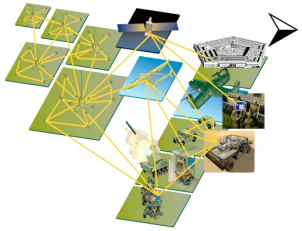
# What is data mining

| Name | Equal To | Size(In Bytes) |
|---|---|---|
| Bit | 1 Bit | 1/8 |
| Nibble | 4 Bits | 1/2 (rare) |
| Byte | 8 Bits | 1 |
| Kilobyte | 1024 Bytes | 1024 |
| Megabyte | 1, 024 Kilobytes | 1, 048, 576 |
| Gigabyte | 1, 024 Megabytes | 1, 073, 741, 824 |
| Terra byte | 1, 024 Gigabytes | 1, 099, 511, 627, 776 |
| Petabyte | 1, 024 Terabytes | 1, 125, 899, 906, 842, 624 |
| Exabyte | 1, 024 Petabytes | 1, 152, 921, 504, 606, 846, 976 |
| Zettabyte | 1, 024 Exabytes | 1, 180, 591, 620, 717, 411, 303, 424 |
| Yottabyte | 1, 024 Zettabytes | 1, 208, 925, 819, 614, 629, 174, 706, 176 |

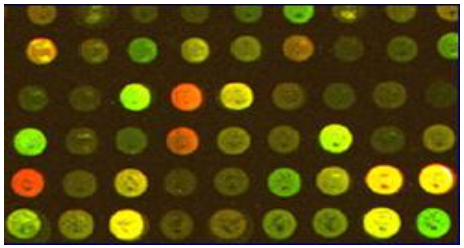
# Why Data Mining?



- 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

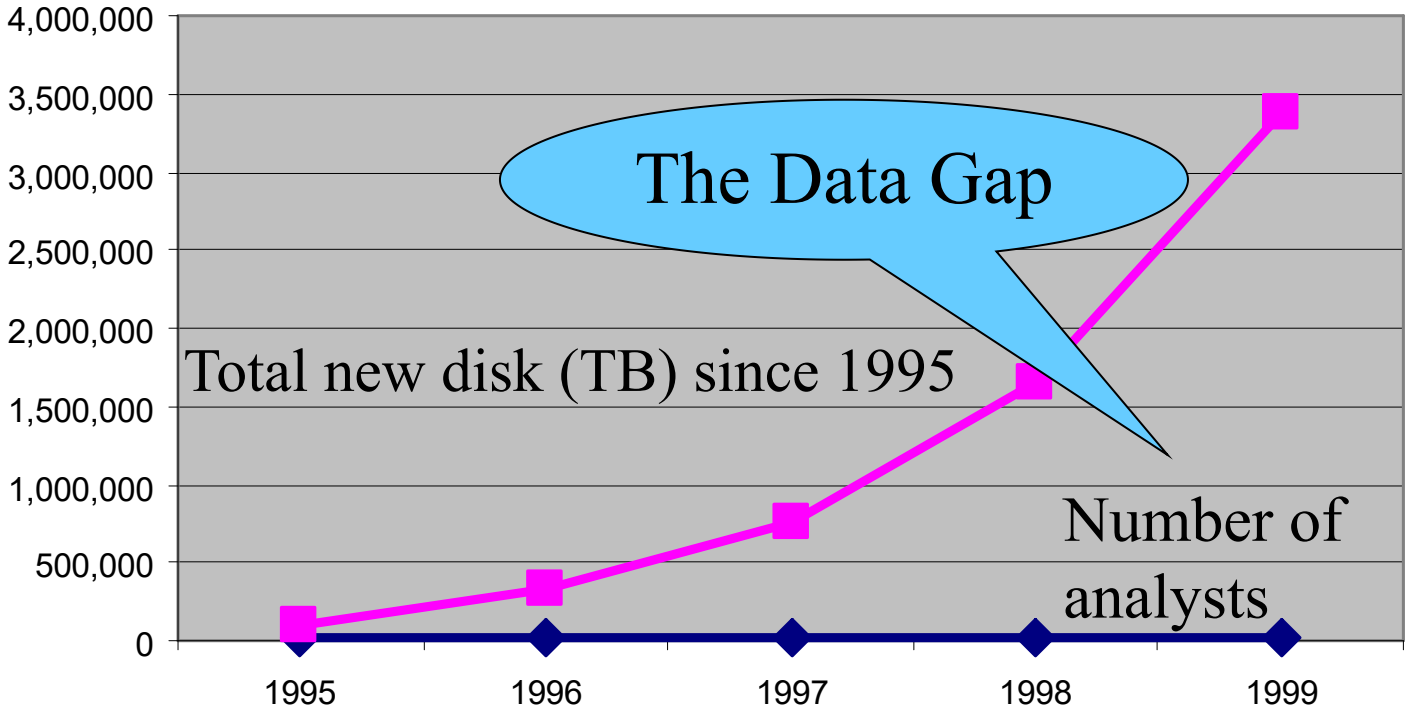

- **We are drowning in data, but starving for knowledge !**
- "Necessity is the mother of invention"—Data mining—Automated analysis of massive data sets



# Why Data Mining?



- There is often information "hidden" in the data that is not readily evident
- Human analysts may take weeks to discover useful information
- Much of the data is never analyzed at all



# What Is Data Mining?



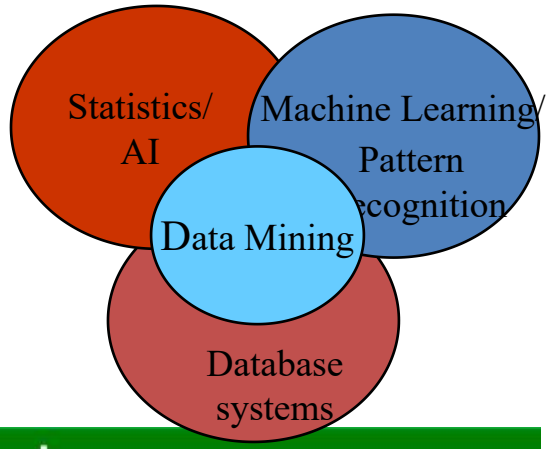
- Data mining (knowledge discovery from data)
  - Extraction of interesting (non-trivial, implicit, previously unknown and potentially useful) patterns or knowledge from huge amount of data
  - Data mining: a misnomer?
- Alternative names
  - Knowledge discovery (mining) in databases (KDD), knowledge extraction, data/pattern analysis, data archeology, data dredging, information harvesting, business intelligence, etc.
- Watch out: Is everything "data mining"?
  - Simple search and query processing
  - (Deductive) expert systems

# What Is Data Mining?



- **What is not Data Mining?**
  - Look up phone number in phone directory
  - Query a Web search engine for information about "Amazon"
- Origin of Data Mining
  - Draws ideas from machine learning/AI, pattern recognition, statistics, and database systems
  - Traditional Techniques may be unsuitable due to
    - Enormity of data
    - High dimensionality of data
    - Heterogeneous, distributed nature of data

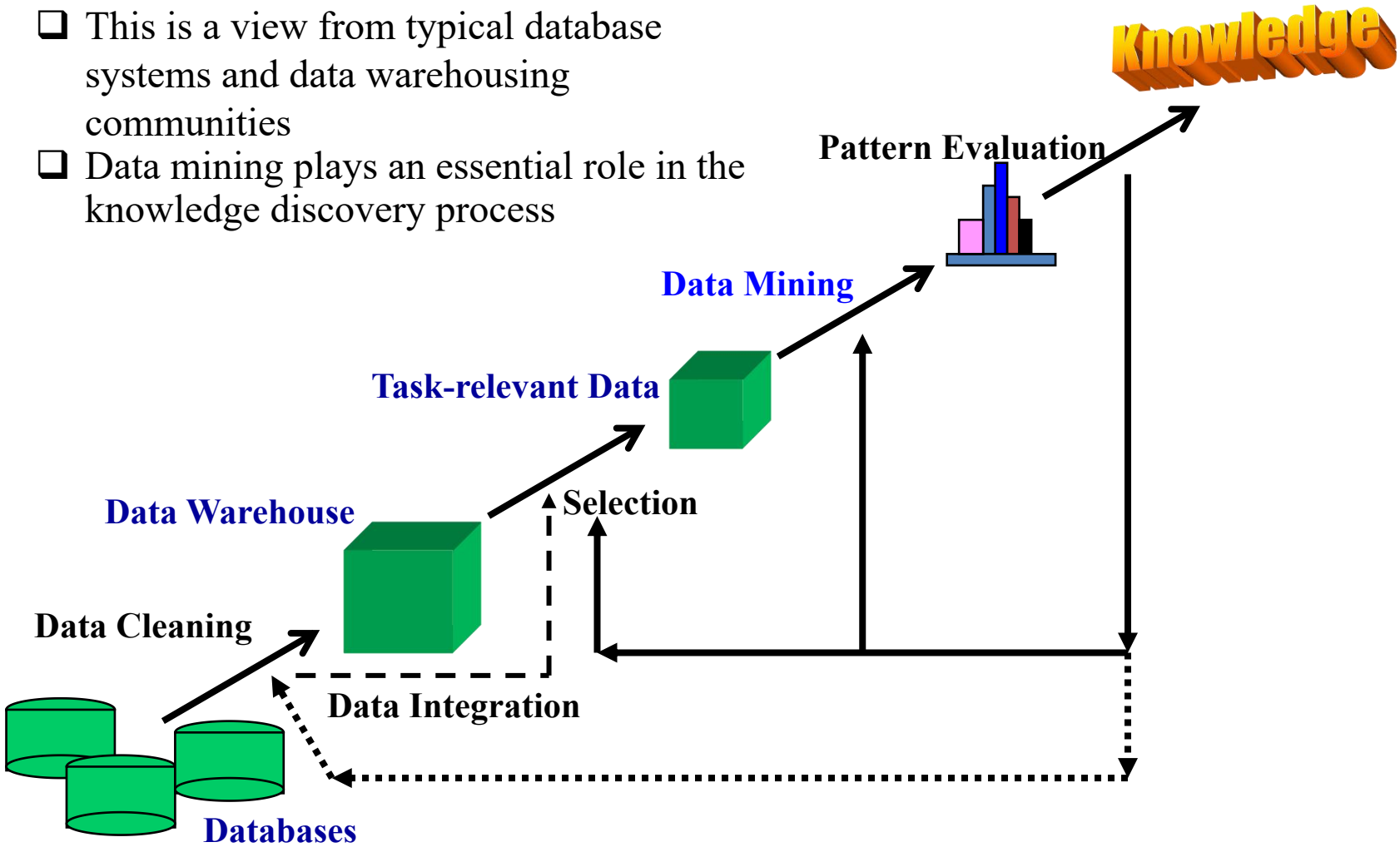
- **What is Data Mining?**
  - Certain names are more prevalent in certain US locations (O'Brien, O'Rurke, O'Reilly… in Boston area)
  - Group together similar documents returned by search engine according to their context (e.g. Amazon rainforest, Amazon.com,)



# Knowledge Discovery (KDD) Process

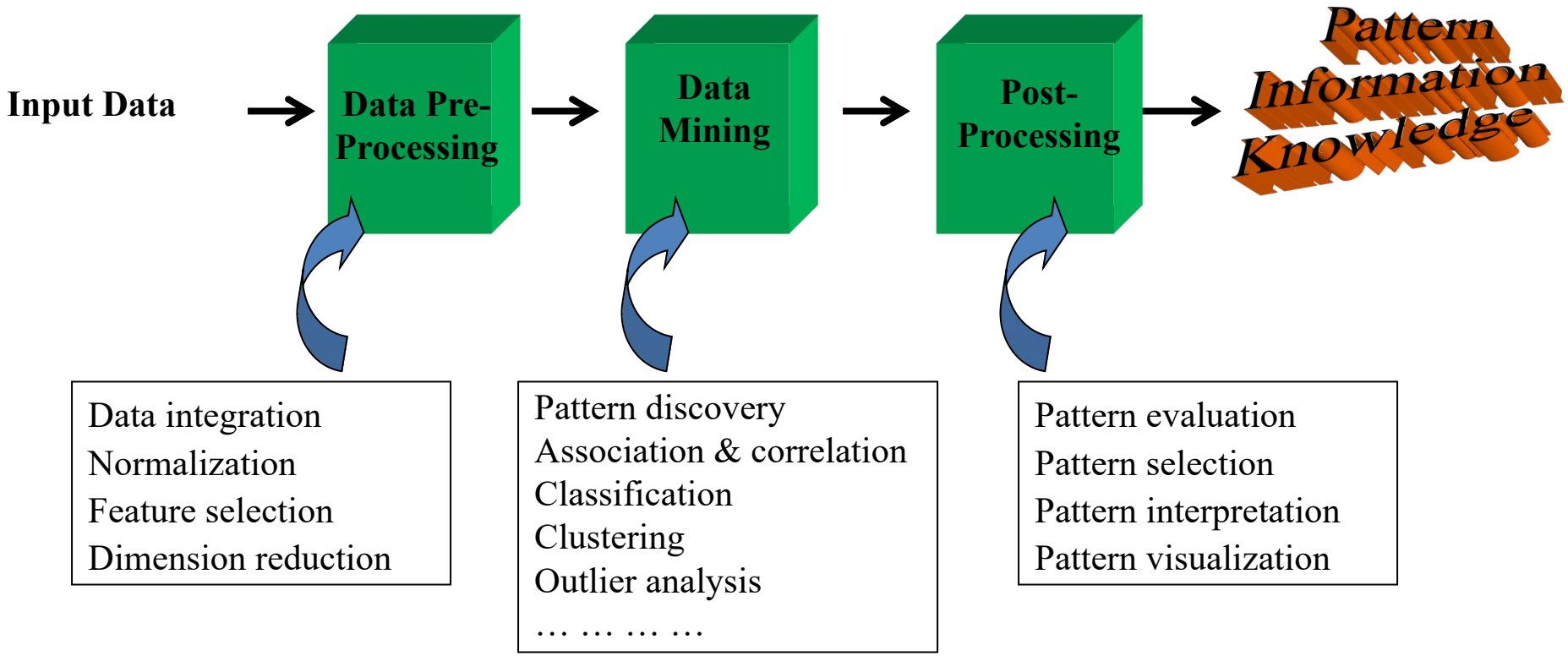


- This is a view from typical database systems and data warehousing communities
- Data mining plays an essential role in the knowledge discovery process



# KDD Process: A Typical View from ML and Statistics






- **Example:** Health care & medical data mining – often adopted such a view in statistics and machine learning
  - Preprocessing of the data (including feature extraction and dimension reduction)
  - Classification or/and clustering processes
  - Post-processing for presentation

# Multi-Dimensional View of Data Mining



- **Data to be mined**
  - Database data (extended-relational, object-oriented, heterogeneous, legacy), 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, trend/deviation, outlier analysis, etc.
  - 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.

# Data Mining: On What Kinds of Data?



- Database-oriented data sets and applications
  - Relational database, data warehouse, transactional database
- Advanced data sets and advanced applications
  - Data streams and sensor data
  - Time-series data, temporal data, sequence data (incl. bio-sequences)
  - Structure data, graphs, social networks and multi-linked data
  - Object-relational databases
  - Heterogeneous databases and legacy databases
  - Spatial data and spatiotemporal data
  - Multimedia database
  - Text databases
  - The World-Wide Web

# Data Mining Tasks



- Prediction Methods
  - Use some variables to predict unknown or future values of other variables.
    - Classification
    - Regression
    - Deviation Detection
- Description Methods
  - Find human-interpretable patterns that describe the data.
    - Clustering
    - Association Rule Discovery
    - Sequential Pattern Discovery

# Data Mining Function: (1) Generalization



- 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

# (2) Association and Correlation Analysis



- Frequent patterns (or frequent itemsets)
  - What items are frequently purchased together in your Walmart?
- Association, correlation vs. causality
  - 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?

| *TID* | *Items* |
|---|---|
| 1 | Bread, Coke, Milk |
| 2 | Beer, Bread |
| 3 | Beer, Coke, Diaper, Milk |
| 4 | Beer, Bread, Diaper, Milk |
| 5 | Coke, Diaper, Milk |

Rules Discovered:

{Milk} --> {Coke}

{Diaper, Milk} --> {Beer}

# (3) Classification



- 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), or 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, …

# (3) Classification - Regression



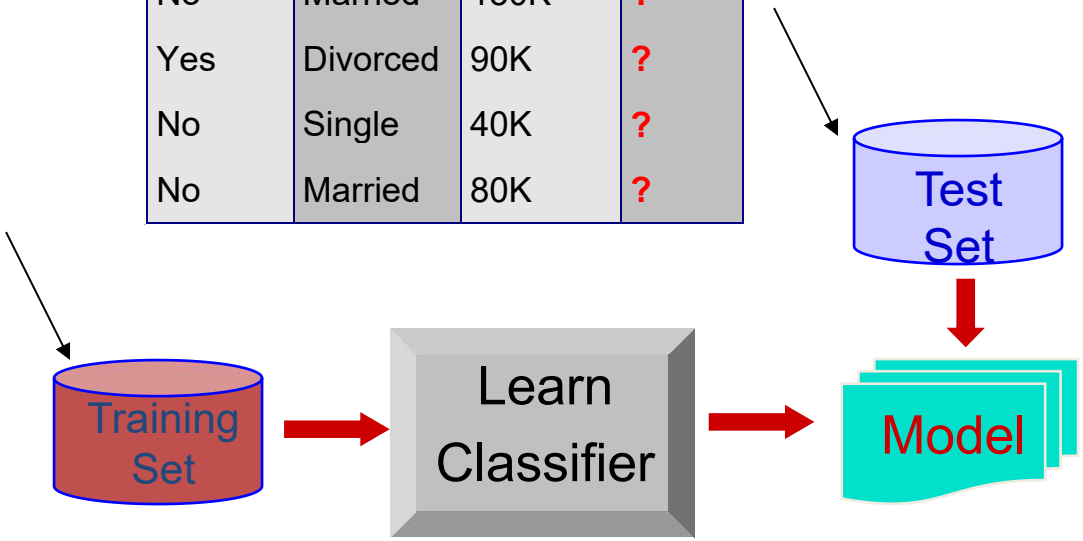
- Predict a value of a given continuous valued variable based on the values of other variables, assuming a linear or nonlinear model of dependency.
- Greatly studied in statistics, neural network fields.
- Examples:
  - Predicting sales amounts of new product based on advetising expenditure.
  - Predicting wind velocities as a function of temperature, humidity, air pressure, etc.
  - Time series prediction of stock market indices.


# (3) Classification Example



| Tid | Refund (categorical) | Marital Status (categorical) | Taxable Income (continuous) | Cheat (class) |
|---|---|---|---|---|
| 1 | Yes | Single | 125K | No |
| 2 | No | Married | 100K | No |
| 3 | No | Single | 70K | No |
| 4 | Yes | Married | 120K | No |
| 5 | No | Divorced | 95K | Yes |
| 6 | No | Married | 60K | No |
| 7 | Yes | Divorced | 220K | No |
| 8 | No | Single | 85K | Yes |
| 9 | No | Married | 75K | No |
| 10 | No | Single | 90K | Yes |

| Refund | Marital Status | Taxable Income | Cheat |
|---|---|---|---|
| No | Single | 75K | ? |
| Yes | Married | 50K | ? |
| No | Married | 150K | ? |
| Yes | Divorced | 90K | ? |
| No | Single | 40K | ? |
| No | Married | 80K | ? |



# (4) 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

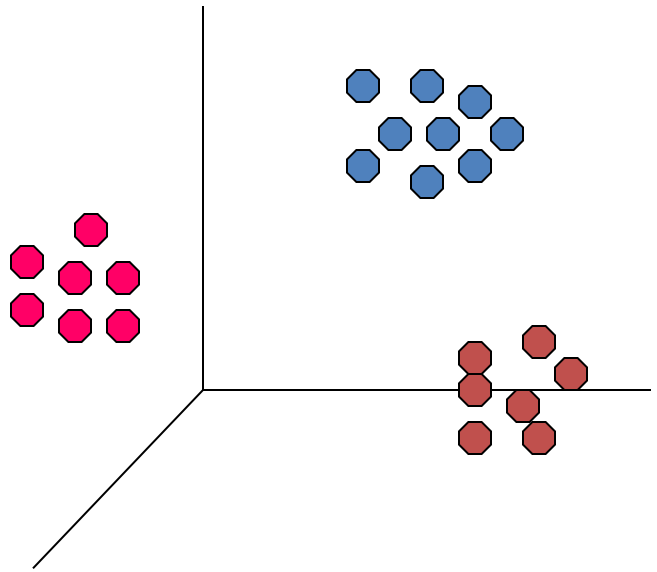
# (4) Cluster Analysis Illustration



- Euclidean Distance Based Clustering in 3-D space.

Intracluster distances are minimized

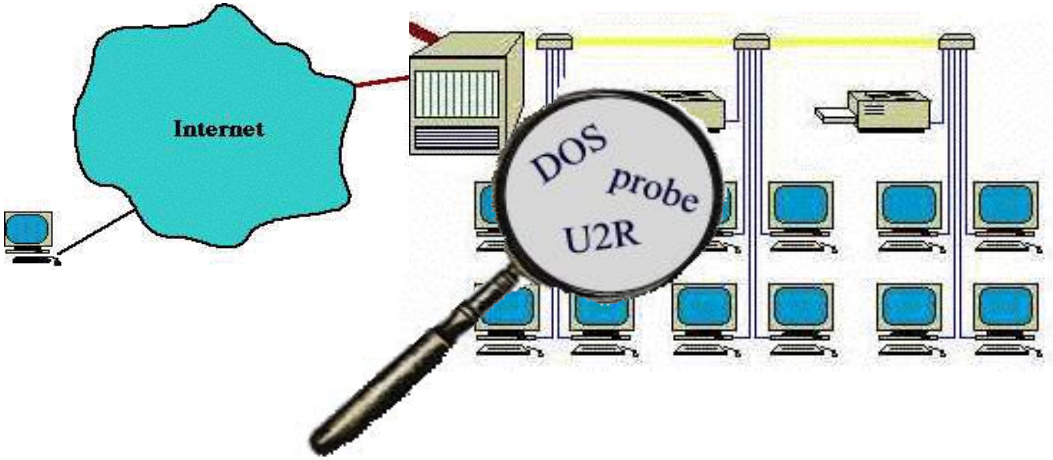
Intercluster distances are maximized



# (5) Outlier Analysis



- 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 network intrusion detection, credit card fraud detection, rare events analysis




# Time and Ordering:



- **Sequential Pattern, Trend and Evolution Analysis**
  - Trend, time-series, and deviation analysis: e.g., regression and value prediction
  - Sequential pattern mining
    - ✓ e.g., first buy digital camera, then buy large SD 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

# 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
    - ✓ A person could be multiple information networks: friends, family, classmates, …
  - Links carry a lot of semantic information: Link mining
- Web mining
  - Web is a big information network: from PageRank to Google
  - Analysis of Web information networks
    - ✓ Web community discovery, opinion mining, usage mining, …

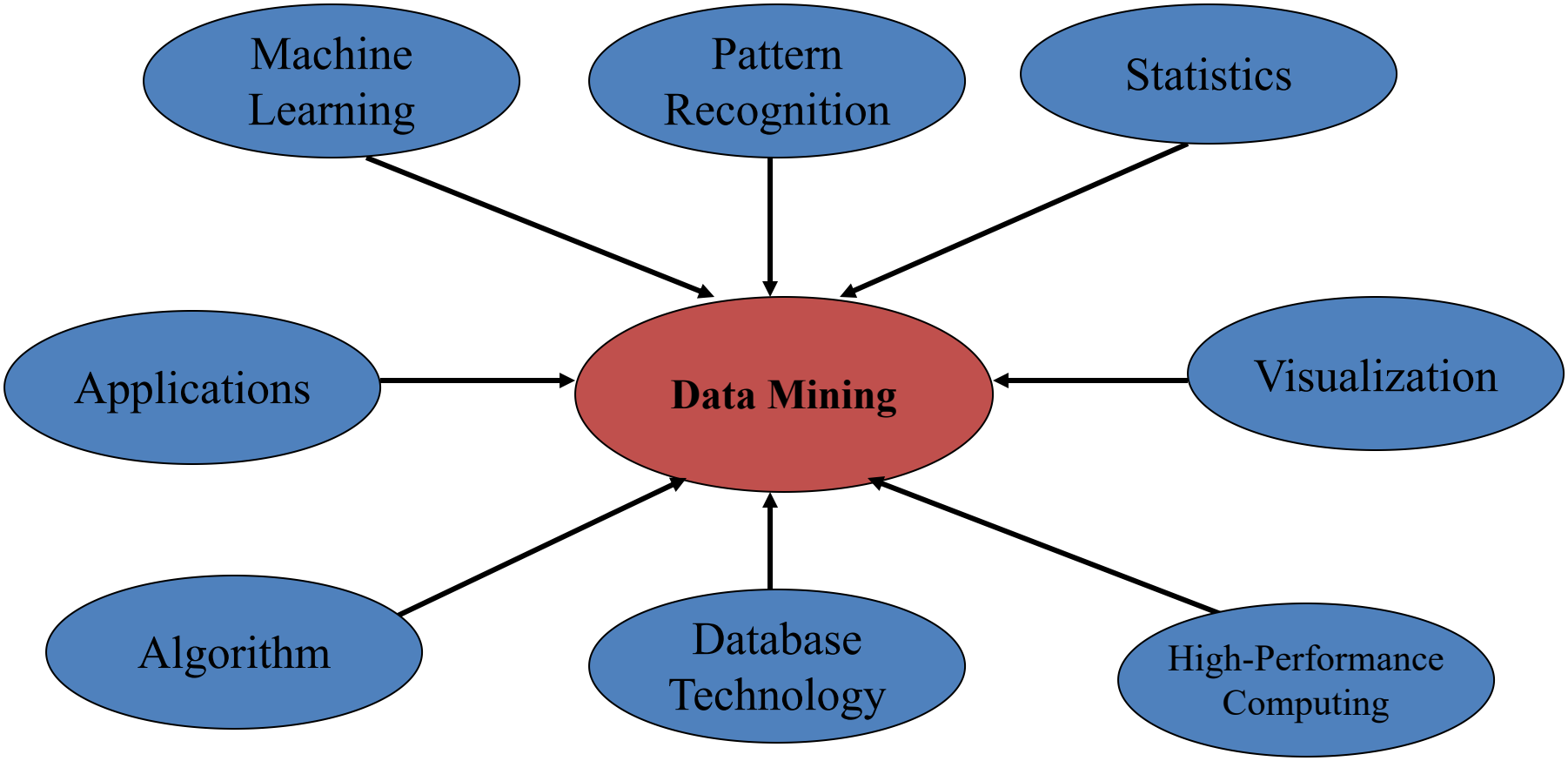
# Evaluation of Knowledge



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

# Data Mining: Confluence of Multiple Disciplines





# Why Confluence of Multiple Disciplines?



- Tremendous amount of data
  - Algorithms must be highly scalable to handle such as tera-bytes of 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 networks and multi-linked data
  - Heterogeneous databases and legacy databases
  - Spatial, spatiotemporal, multimedia, text and Web data
  - Software programs, scientific simulations
- New and sophisticated applications

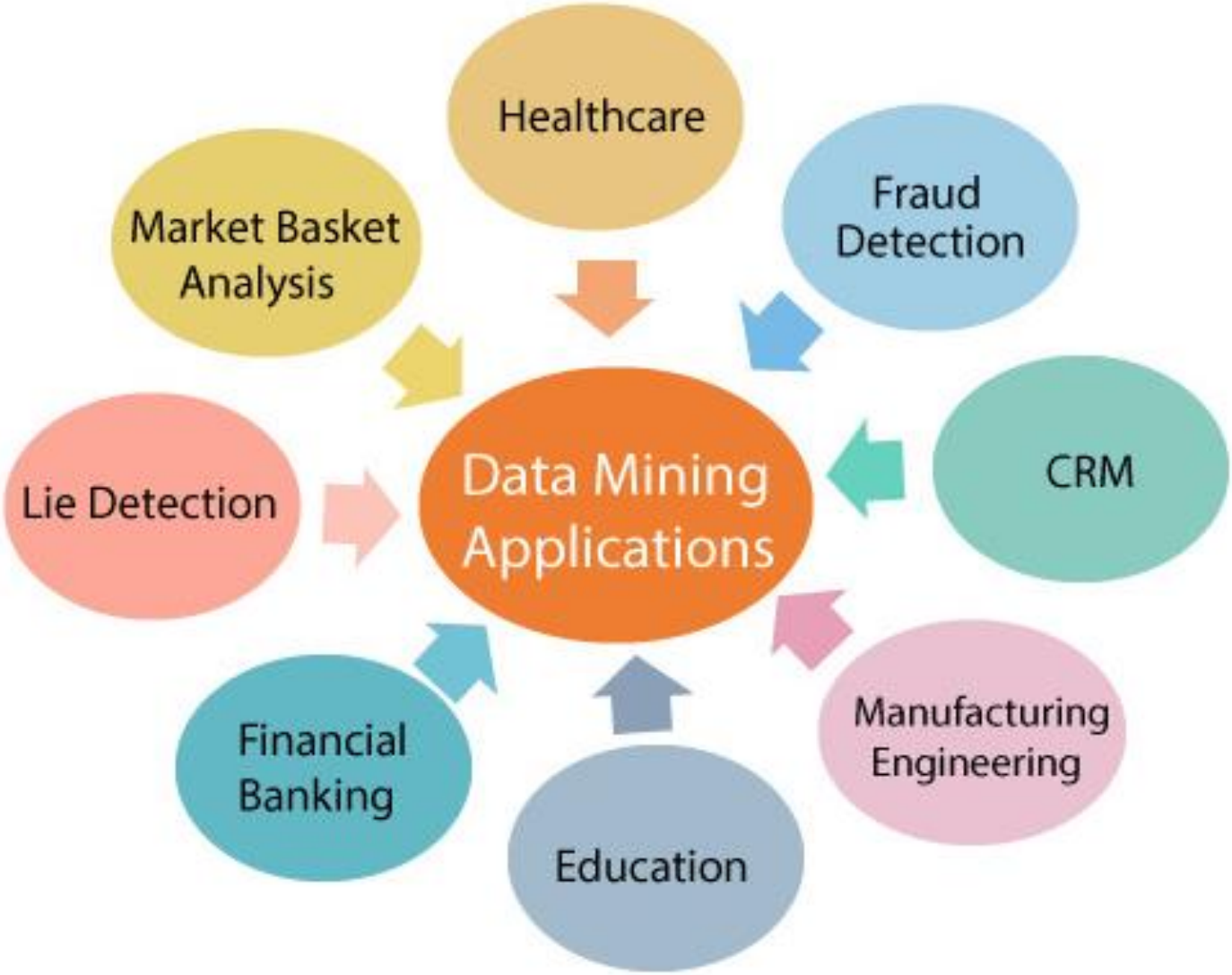

STATISTICS
DATA MINING
ARTIFICIAL INTELLIGENCE
MACHINE LEARNING

# Applications of Data Mining



- Web page analysis: from web page classification, clustering to PageRank & HITS algorithms
- Collaborative analysis & recommender systems
- Basket data analysis to targeted marketing
- Biological and medical data analysis: classification, cluster analysis (microarray data analysis), biological sequence analysis, biological network analysis
- Data mining and software engineering (e.g., IEEE Computer, Aug. 2009 issue)
- From major dedicated data mining systems/tools (e.g., SAS, MS SQL-Server Analysis Manager, Oracle Data Mining Tools) to invisible data mining

# APPLICATION OF DATA MINING



# Major Issues in Data Mining (1)



- Mining Methodology
  - Mining various and new kinds of knowledge
  - Mining knowledge in multi-dimensional space
  - Data mining: An interdisciplinary effort
  - Boosting the power of discovery in a networked environment
  - Handling noise, uncertainty, and incompleteness of data
  - Pattern evaluation and pattern- or constraint-guided mining
- User Interaction
  - Interactive mining
  - Incorporation of background knowledge
  - Presentation and visualization of data mining results

# Major Issues in Data Mining (2)



- Efficiency and Scalability
  - Efficiency and scalability of data mining algorithms
  - Parallel, distributed, stream, and incremental mining methods
- Diversity of data types
  - Handling complex types of data
  - Mining dynamic, networked, and global data repositories
- Data mining and society
  - Social impacts of data mining
  - Privacy-preserving data mining
  - Invisible data mining

# Summary



- Data mining: Discovering interesting patterns and knowledge from massive amount of data
- A natural evolution of database technology, in great demand, with wide applications
- A KDD process includes data cleaning, data integration, data selection, transformation, data mining, pattern evaluation, and knowledge presentation
- Mining can be performed in a variety of data
- Data mining functionalities: characterization, discrimination, association, classification, clustering, outlier and trend analysis, etc.
- Data mining technologies and applications
- Major issues in data mining

# Recommended Text and Reference Books



- **Text Book:**
  - J. Han and M. Kamber. Data Mining: Concepts and Techniques. Morgan Kaufmann, 3rd ed., 2011
- **Reference Books:**
  - H. Dunham. Data Mining: Introductory and Advanced Topics. Pearson Education. 2006.
  - I. H. Witten and E. Frank. Data Mining: Practical Machine Learning Tools and Techniques. Morgan Kaufmann. 2000.
  - D. Hand, H. Mannila and P. Smyth. Principles of Data Mining.Prentice-Hall. 2001.

# Chapter Contents

# What is Data?



- Collection of **data objects** and their **attributes**
- An **attribute** is a property or characteristic of an object
  - Examples: eye color of a person, temperature, etc.
  - Attribute is also known as variable, field, characteristic, or feature
- A collection of attributes describe an **object**
  - Object is also known as record, point, case, sample, entity, or instance

Attributes

Objects

| *Tid* | Refund | Marital Status | Taxable Income | Cheat |
|---|---|---|---|---|
| 1 | Yes | Single | 125K | No |
| 2 | No | Married | 100K | No |
| 3 | No | Single | 70K | No |
| 4 | Yes | Married | 120K | No |
| 5 | No | Divorced | 95K | Yes |
| 6 | No | Married | 60K | No |
| 7 | Yes | Divorced | 220K | No |
| 8 | No | Single | 85K | Yes |
| 9 | No | Married | 75K | No |
| 10 | No | Single | 90K | Yes |

# Data Objects & Attribute



- Data sets are made up of data objects.
- A **data object** represents an entity.
- Examples:
  - ✓ sales database: customers, store items, sales
  - ✓ medical database: patients, treatments
  - ✓ university database: students, professors, courses
- Also called *samples , examples, instances, data points, objects, tuples*.
- Data objects are described by **attributes**.
- Database rows -> data objects; columns ->attributes.
- **Attribute (**or **dimensions, features, variables**): a data field, representing a characteristic or feature of a data object.

  *E.g., customer _ID, name, address*
- Types:
  - ➢ Nominal
  - ➢ Binary
  - ➢ Numeric: quantitative
    - ✓ Interval-scaled, Ratio-scaled

# Attribute Values



- Attribute values are numbers or symbols assigned to an attribute
- Distinction between attributes and attribute values
  - Same attribute can be mapped to different attribute values
    - ✓ Example: height can be measured in feet or meters
  - Different attributes can be mapped to the same set of values
    - ✓ Example: Attribute values for ID and age are integers
    - ✓ But properties of attribute values can be different
      - ✓ ID has no limit but age has a maximum and minimum value

# Types of Attributes



- There are different types of attributes
  - Nominal
    - ✓ Examples: ID numbers, eye color, zip codes
  - Ordinal
    - ✓ Examples: rankings (e.g., taste of potato chips on a scale from 1-10), grades, height in {tall, medium, short}
  - Interval
    - ✓ Examples: calendar dates, temperatures in Celsius or Fahrenheit.
  - Ratio
    - ✓ Examples: temperature in Kelvin, length, time, counts

# Types of Attributes...



- **Nominal :** Nominal means relating to names. The values of Nominal attributes are symbols or names of things. For example:
  - ✓ *Hair_color = {auburn, black, blond, brown, grey, red, white}*
  - ✓ marital status, occupation, ID numbers, zip codes
  - ✓ The values don't have any meaningful order about them.
- **Binary:** Nominal attribute woth only two states (0 and 1), where 0 typically means the attribute is absent, and 1 means that it is present. Binary attributes are reffered to as Boolean if the two states correspond to true and false.
  - ➢ **Symmetric binary:** both outcomes equally important
    - ✓ e.g., gender
  - ➢ **Asymmetric binary:** outcomes not equally important.
    - ✓ e.g., medical test (positive vs. negative)
    - ✓ Convention: assign 1 to most important outcome (e.g., HIV positive)

# Types of Attributes...



- **Ordinal**
  - ✓ Values have a meaningful order (ranking) but magnitude between successive values is not known.
  - ✓ Size = {small, medium, large}, grades, army rankings
  - ✓ Other examples of ordinal attributes include Grade (e.g., A+, A, A−, B+, and so on) and Professional rank. Professional ranks can be enumerated in a sequential order, such as assistant, associate, and full for professors,
- The central tendency of an ordinal attribute can be represented by its mode and its median (the middle value in an ordered sequence), but the mean cannot be defined.
- Qualitative attributes are describes a feature of an object, without giving an actual size or quantity. The values of such qualitative attributes are typically words representing categories.

# Types of Attributes...



- Quantity (integer or real-valued)
- **Interval**
  - Measured on a scale of **equal-sized units**
  - Values have order
    - ✓ E.g., *temperature in C˚or F˚, calendar dates*
  - No true zero-point
- **Ratio**
  - Inherent **zero-point**
  - We can speak of values as being an order of magnitude larger than the unit of measurement (10 K˚ is twice as high as 5 K˚).
    - ✓ e.g., *temperature in Kelvin, length, counts, monetary quantities*

# Properties of Attribute Values



- The type of an attribute depends on which of the following properties it possesses:

| | |
|---|---|
| Distinctness: | = ≠ |
| Order: | < > |
| Addition: | + - |
| Multiplication: | * / |

- Nominal attribute: distinctness
- Ordinal attribute: distinctness & order
- Interval attribute: distinctness, order & addition
- Ratio attribute: all 4 properties

# Properties of Attribute Values...



| Attribute Type | Description | Examples | Operations |
|---|---|---|---|
| Nominal | The values of a nominal attribute are just different names, i.e., nominal attributes provide only enough information to distinguish one object from another. (=, ≠) | zip codes, employee ID numbers, eye color, sex: {male, female} | mode, entropy, contingency correlation, $\chi 2$ test |
| Ordinal | The values of an ordinal attribute provide enough information to order objects. (<, >) | hardness of minerals, {good, better, best}, grades, street numbers | median, percentiles, rank correlation, run tests, sign tests |
| Interval | For interval attributes, the differences between values are meaningful, i.e., a unit of measurement exists. (+, - ) | calendar dates, temperature in Celsius or Fahrenheit | mean, standard deviation, Pearson's correlation, t and F tests |
| Ratio | For ratio variables, both differences and ratios are meaningful. (*, /) | temperature in Kelvin, monetary quantities, counts, age, mass, length, electrical current | geometric mean, harmonic mean, percent variation |

# Properties of Attribute Values...



| Attribute Level | Transformation | Comments |
|---|---|---|
| Nominal | Any permutation of values | If all employee ID numbers were reassigned, would it make any difference? |
| Ordinal | An order preserving change of values, i.e., new_value = f(old_value) where f is a monotonic function. | An attribute encompassing the notion of good, better best can be represented equally well by the values {1, 2, 3} or by { 0.5, 1, 10}. |
| Interval | new_value =a * old_value + b where a and b are constants | Thus, the Fahrenheit and Celsius temperature scales differ in terms of where their zero value is and the size of a unit (degree). |
| Ratio | new_value = a * old_value | Length can be measured in meters or feet. |

# Discrete and Continuous Attributes



- Discrete Attribute
  - Has only a finite or countably infinite set of values
  - Examples: zip codes, counts, or the set of words in a collection of documents
  - Often represented as integer variables.
  - Note: binary attributes are a special case of discrete attributes

- Continuous Attribute
  - Has real numbers as attribute values
  - Examples: temperature, height, or weight.
  - Practically, real values can only be measured and represented using a finite number of digits.
  - Continuous attributes are typically represented as floating-point variables.

# Types of data sets



- Record
  - Relational records
  - Data matrix, e.g., numerical matrix, crosstabs
  - Document data: text documents: term-frequency vector
  - Transaction data
- Graph
  - World Wide Web
  - Social and infomation network
  - Molecular Structures
- Ordered
  - Video data: sequence of images
  - Temporal data: time-series
  - Sequential Data: transaction sequences
  - Genetic sequence data
- Spatial, image and multimedia
  - Spatial data: maps
  - Image data

# Important Characteristics of Structured Data



- Dimensionality
  - Curse of Dimensionality
- Sparsity
  - Only presence counts
- Resolution
  - Patterns depend on the scale
- Distribution
  - Centrality and dispersion

# Record Data



- Data that consists of a collection of records, each of which consists of a fixed set of attributes

| *Tid* | Refund | Marital Status | Taxable Income | Cheat |
|---|---|---|---|---|
| 1 | Yes | Single | 125K | No |
| 2 | No | Married | 100K | No |
| 3 | No | Single | 70K | No |
| 4 | Yes | Married | 120K | No |
| 5 | No | Divorced | 95K | Yes |
| 6 | No | Married | 60K | No |
| 7 | Yes | Divorced | 220K | No |
| 8 | No | Single | 85K | Yes |
| 9 | No | Married | 75K | No |
| 10 | No | Single | 90K | Yes |

# Data Matrix



- If data objects have the same fixed set of numeric attributes, then the data objects can be thought of as points in a multi-dimensional space, where each dimension represents a distinct attribute
- Such data set can be represented by an m by n matrix, where there are m rows, one for each object, and n columns, one for each attribute

| Projection of x Load | Projection of y load | Distance | Load | Thickness |
|---|---|---|---|---|
| 10.23 | 5.27 | 15.22 | 2.7 | 1.2 |
| 12.65 | 6.25 | 16.22 | 2.2 | 1.1 |

# Document Data



- Each document becomes a `term' vector,
  - each term is a component (attribute) of the vector,
  - the value of each component is the number of times the corresponding term occurs in the document.

| | team | coach | play | ball | score | game | win | lost | timeout | season |
|---|---|---|---|---|---|---|---|---|---|---|
| Document 1 | 3 | 0 | 5 | 0 | 2 | 6 | 0 | 2 | 0 | 2 |
| Document 2 | 0 | 7 | 0 | 2 | 1 | 0 | 0 | 3 | 0 | 0 |
| Document 3 | 0 | 1 | 0 | 0 | 1 | 2 | 2 | 0 | 3 | 0 |

# Transaction Data



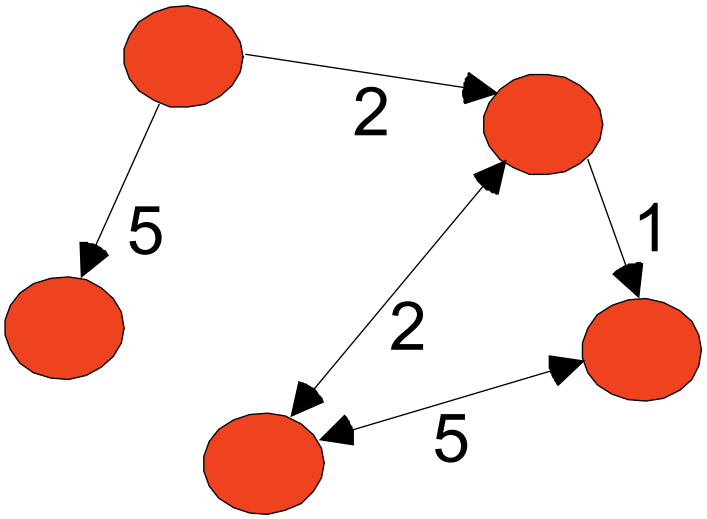
- A special type of record data, where
  - each record (transaction) involves a set of items.
  - For example, consider a grocery store. The set of products purchased by a customer during one shopping trip constitute a transaction, while the individual products that were purchased are the items.

| *TID* | *Items* |
|---|---|
| 1 | Bread, Coke, Milk |
| 2 | Beer, Bread |
| 3 | Beer, Coke, Diaper, Milk |
| 4 | Beer, Bread, Diaper, Milk |
| 5 | Coke, Diaper, Milk |

# Graph Data



- Examples: Generic graph and HTML Links




**Useful Links:**

- Bibliography
- Other Useful Web sites
  - ACM SIGKDD
  - KDnuggets
  - The Data Mine

**Knowledge Discovery and Data Mining Bibliography**
(Gets updated frequently, so visit often!)

- Books
- General Data Mining

**Book References in Data Mining and Knowledge Discovery**

Usama Fayyad, Gregory Piatetsky-Shapiro, Padhraic Smyth, and Ramasamy uthurasamy, "Advances in Knowledge Discovery and Data Mining", AAAI Press/the MIT Press, 1996.

J. Ross Quinlan, "C4.5: Programs for Machine Learning", Morgan Kaufmann Publishers, 1993. Michael Berry and Gordon Linoff, "Data Mining Techniques (For Marketing, Sales, and Customer Support), John Wiley & Sons, 1997.

**General Data Mining**

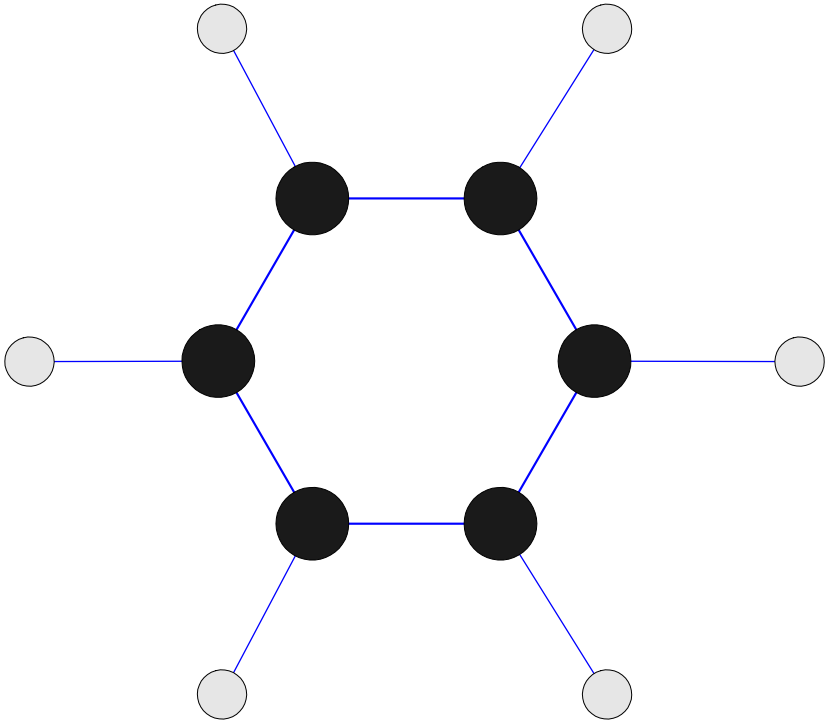
Usama Fayyad, "Mining Databases: Towards Algorithms for Knowledge Discovery", Bulletin of the IEEE Computer Society Technical Committee on data Engineering, vol. 21, no. 1, March 1998.

Christopher Matheus, Philip Chan, and Gregory Piatetsky-Shapiro, "Systems for knowledge Discovery in databases", IEEE Transactions on Knowledge and Data Engineering, 5(6):903-913, December 1993.

# Chemical Data



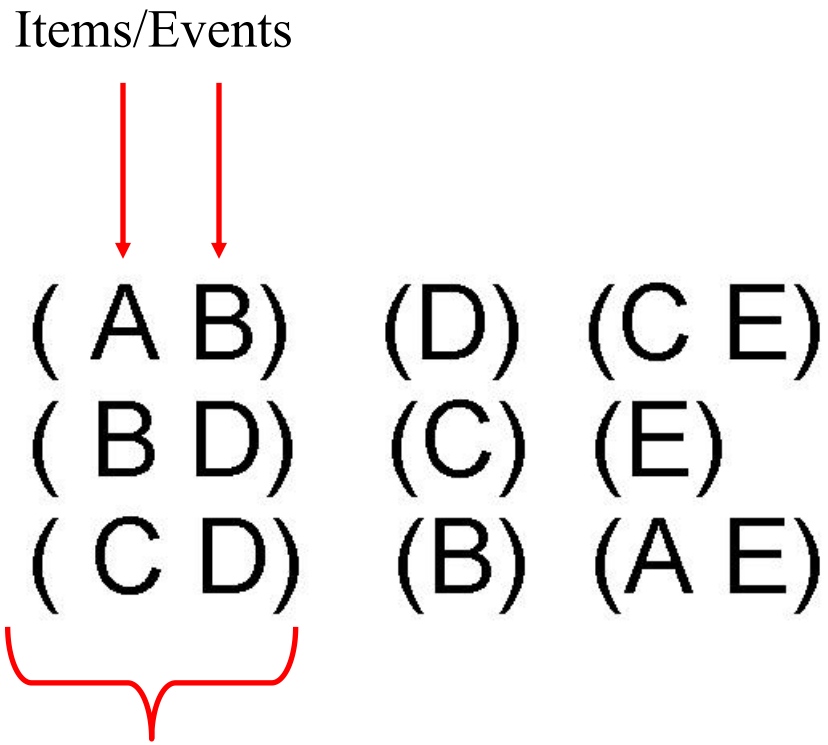
- Benzene Molecule: $C_6H_6$



# Ordered Data



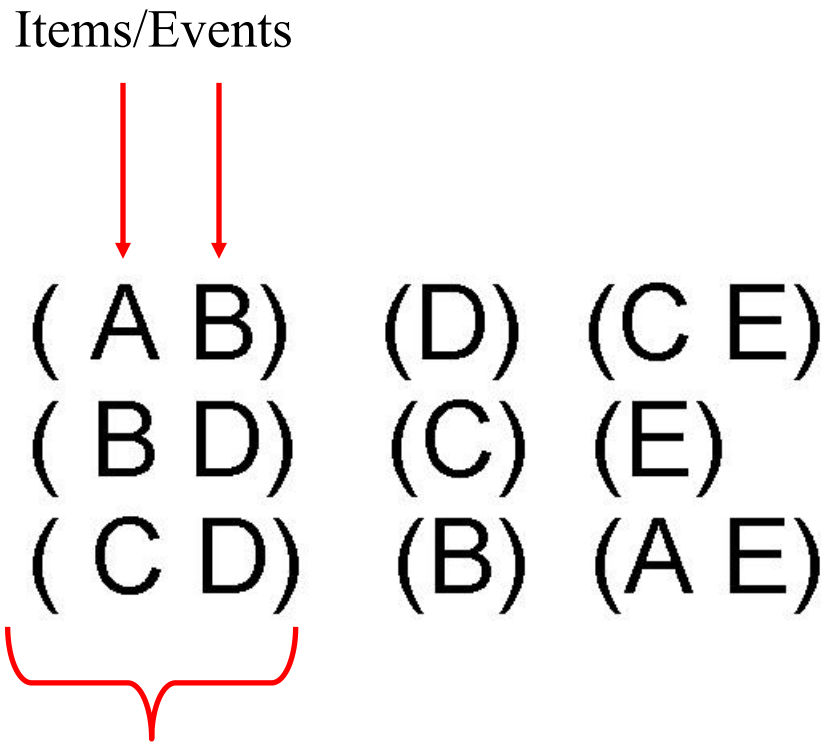
Sequences of transactions



# Ordered Data



Sequences of transactions



# Ordered Data



- Genomic sequence data

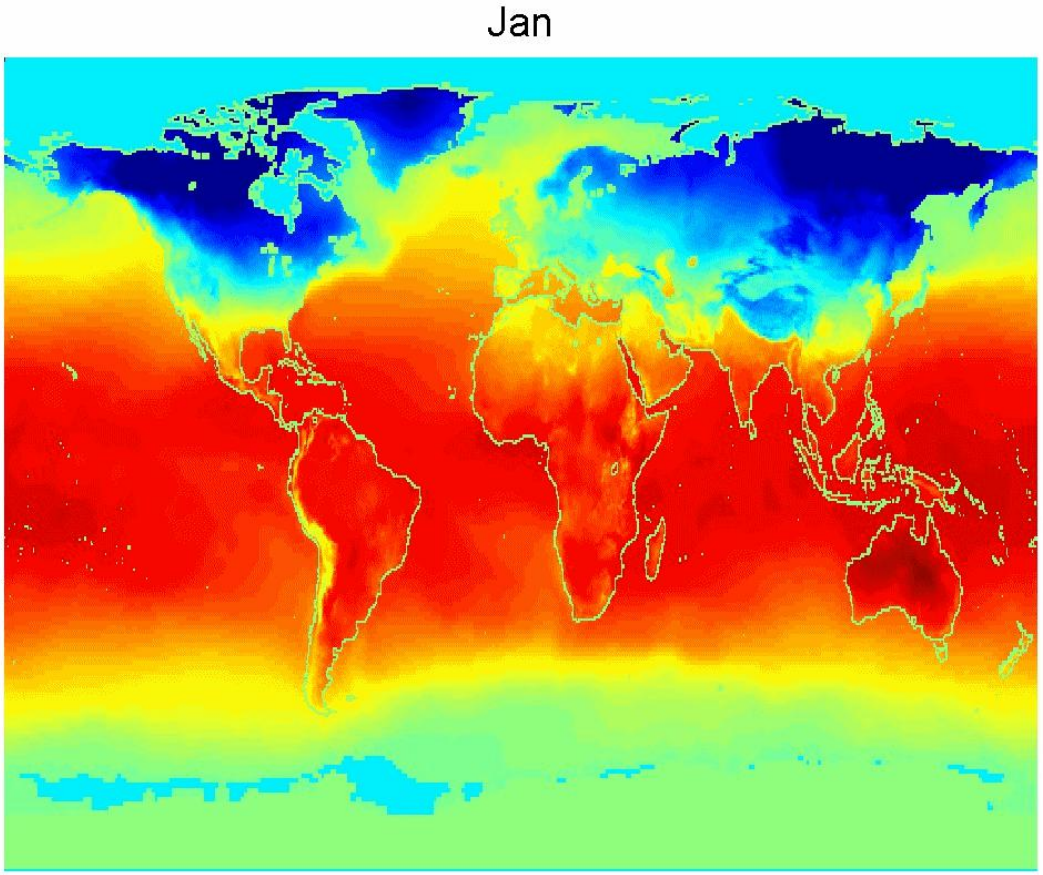
```
GGTTCCGCCTTCAGCCCCGCGCC
CGCAGGGCCCGCCCCGCGCCGTC
GAGAAGGGCCCGCCTGGCGGGCG
GGGGGAGGCGGGGCCGCCCGAGC
CCAACCGAGTCCGACCAGGTGCC
CCCTCTGCTCGGCCTAGACCTGA
GCTCATTAGGCGGCAGCGGACAG
GCCAAGTAGAACACGCGAAGCGC
TGGGCTGCCTGCTGCGACCAGGG
```

# Ordered Data



- Spatio-Temporal Data

Average Monthly Temperature of land and ocean



# Data Quality



- What kinds of data quality problems?
- How can we detect problems with the data?
- What can we do about these problems?

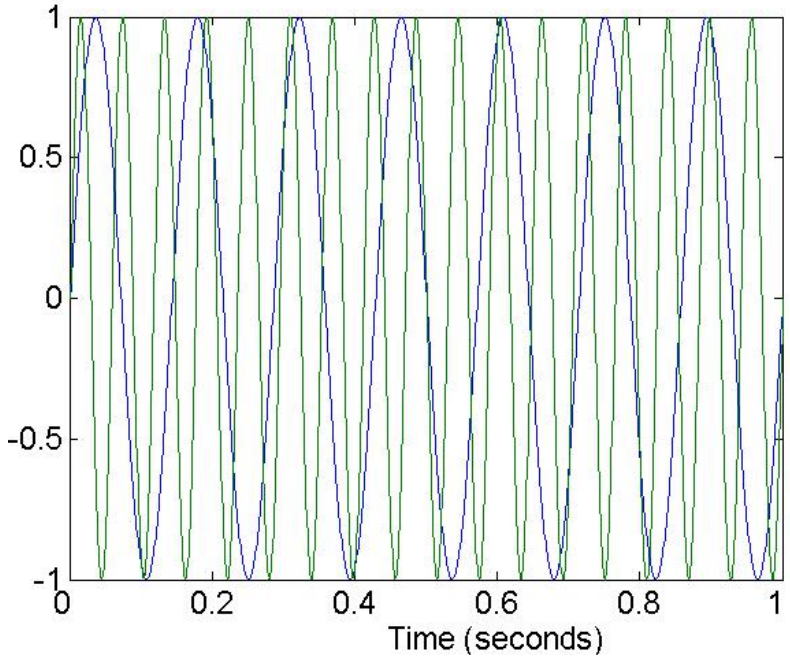
**Data Preparation = Cleaning the Data**

- Data Preparation can take **40-80%** (or more) of the effort in a data mining project
  - ✓ Dealing with NULL (missing) values
  - ✓ Dealing with errors
  - ✓ Dealing with noise
  - ✓ Dealing with outliers (unless that is your science!)
  - ✓ Transformations: units, scale, projections
  - ✓ Data normalization
  - ✓ Relevance analysis: Feature Selection
  - ✓ Remove redundant attributes
  - ✓ Dimensionality Reduction

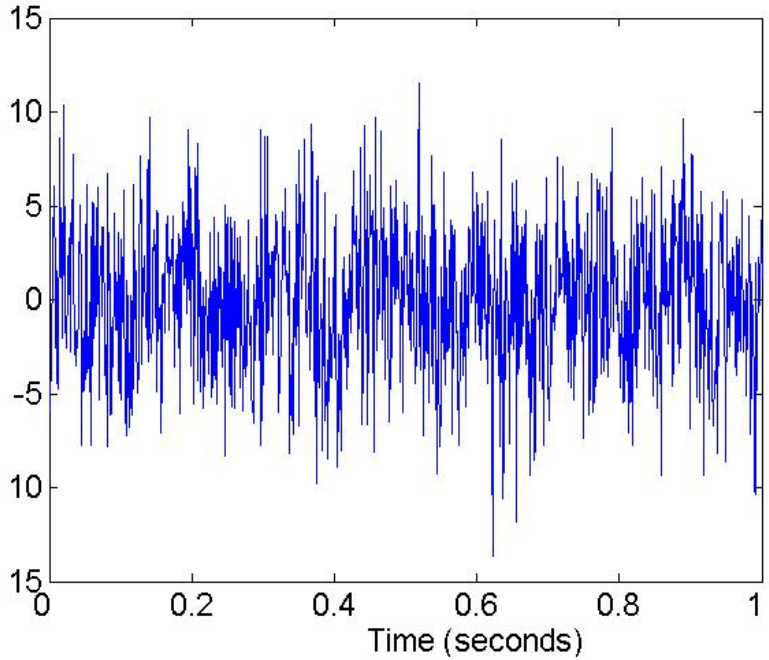
# Noise



- For objects, noise is an extraneous object
- For attibutes, noise refers to modification of original values
  - Examples: distortion of a person's voice when talking on a poor phone and "snow" on television screen




**Two Sine Waves**

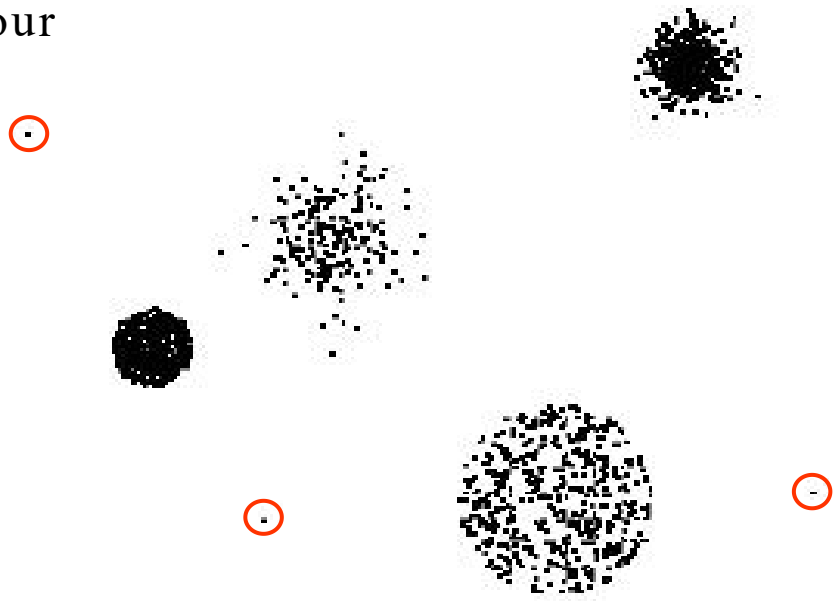



**Two Sine Waves + Noise**

# Outliers



- Outliers are data objects with characteristics that are considerably different than most of the other data objects in the data set
- Case 1: Outliers are noise that interferes with data analysis
- Case 2: Outliers are the goal of our analysis
  - ✓ Credit card fraud
  - ✓ Intrusion detection



# Missing Values



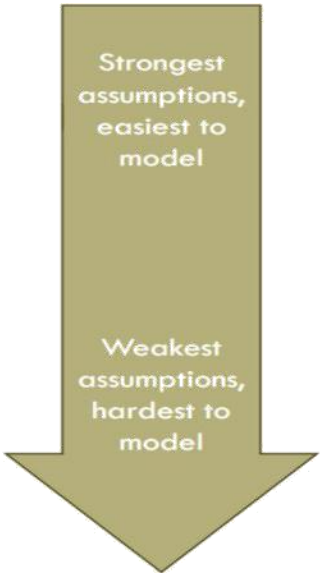
- Reasons for missing values
  - Information is not collected
    (e.g., people decline to give their age and weight)
  - Attributes may not be applicable to all cases
    (e.g., annual income is not applicable to children)

- Handling missing values
  - Eliminate Data Objects
  - Estimate Missing Values
  - Ignore the Missing Value During Analysis
  - Replace with all possible values (weighted by their probabilities)

# Types of Missing Values



- Some definitions are based on representation: Missing data is the lack of a recorded answer for a particular field.
  - Missing completely at random (MCAR)
  - Missing at Random (MAR)
  - Missing Not at Random (MNAR)




"All I know is that you throw out missing data or fill it in and make an informative note of it."

# Missing Completely at Random (MCAR)



- Missingness of a value is independent of attributes
  - ✓ Fill in values based on the attribute
  - ✓ Analysis may be unbiased overall
- The missingness on the variable is completely unsystematic.
- Example when we take a random sample of a population, where each member has the same chance of being included in the sample.

| ID | Gender | Age | Income |
|---|---|---|---|
| 1 | Male | Under 30 | Low |
| 2 | Female | Under 30 | Low |
| 3 | Female | 30 or more | High |
| 4 | Female | 30 or more | |
| 5 | Female | 30 or more | High |

When we make this assumption, we are assuming that whether or not the person has missing data is completely unrelated to the other information in the data.

When data is missing completely at random, it means that we can undertake analyses using only observations that have complete data (provided we have enough of such observations).

# Missing at Random (MAR)



- Missingness is related to other variables
- Fill in values based other values
- Almost always produces a bias in the analysis

***Example of MAR is when we take a sample from a population, where the probability to be included depends on some known property.***

A simple predictive model is that income can be predicted based on gender and age. Looking at the table, we note that our missing value is for a Female aged 30 or more, and observations says the other females aged 30 or more have a High income. As a result, we can predict that the missing value should be High.

| ID | Gender | Age | Income |
|---|---|---|---|
| 1 | Male | Under 30 | Low |
| 2 | Female | Under 30 | Low |
| 3 | Female | 30 or more | High |
| 4 | Female | 30 or more | |
| 5 | Female | 30 or more | High |

There is a systematic relationship between the inclination of missing values and the observed data, but not the missing data. All that is required is a probabilistic relationship

# Missing not at Random (MNAR) - Nonignorable



- Missingness is related to unobserved measurements
- When the missing values on a variable are related to the values of that variable itself, even after controlling for other variables.

***MNAR means that the probability of being missing varies for reasons that are unknown to us.***

Data was obtained from 31 women, of whom 14 were located six months later. Of these, three had exited from homelessness, so the estimated proportion to have exited homelessness is 3/14 = 21%. As there is no data for the 17 women who could not be contacted, it is possible that none, some, or all of these 17 may have exited from homelessness. This means that potentially the proportion to have exited from homelessness in the sample is between 3/31 = 10% and 20/31 = 65%. As a result, reporting 21% as being the correct result is misleading. In this example the missing data is nonignorable.

Strategies to handle MNAR are to find more data about the causes for the missingness, or to perform what-if analyses to see how sensitive the results are under various scenarios.

# Formalize the definitions



- Let's X represent a matrix of the data we "expect" to have; X = {Xo, Xm} where Xo is the observed data and Xm the missing data.
    1. **MCAR: P(R| Xo , Xm ) = P(R)**
    2. **MAR: P(R| Xo , Xm ) = P(R| Xo)**
- Let's define R as a matrix with the same dimensions as X where Ri,j = 1 if the datum is missing, and 0 otherwise.
    3. **MNAR: No simplification.**

# Duplicate Data



- Data set may include data objects that are duplicates, or almost duplicates of one another
  - Major issue when merging data from heterogeous sources
- Examples:
  - ✓ Same person with multiple email addresses
- Data cleaning

  Process of dealing with duplicate data issues
- When should duplicate data not be removed?

# Data Preprocessing



- Aggregation
- Sampling
- Dimensionality Reduction
- Feature subset selection
- Feature creation
- Discretization and Binarization
- Attribute Transformation

# Aggregation

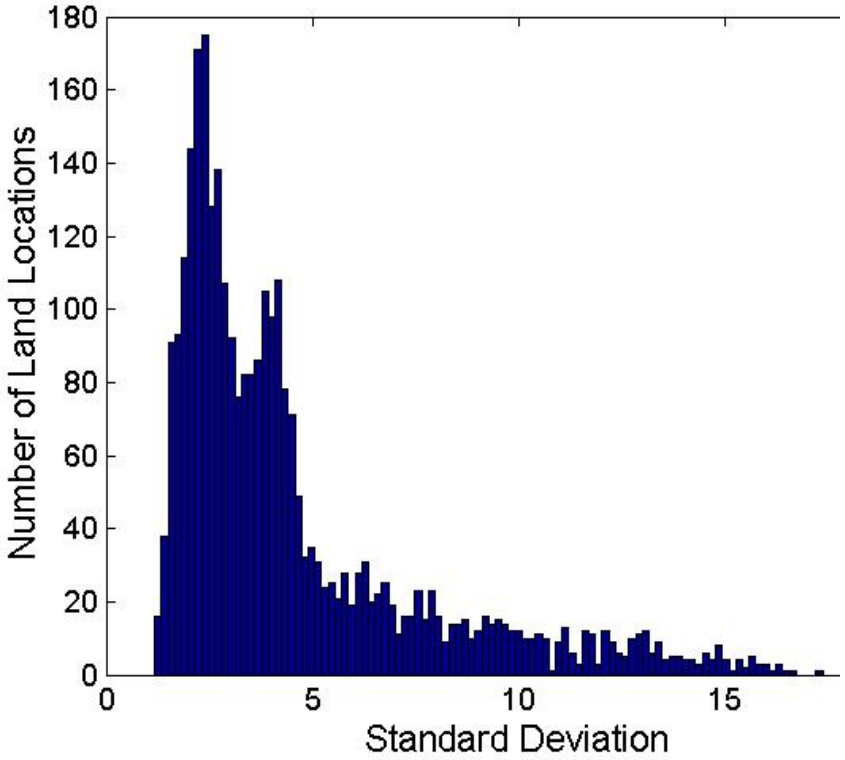


- Combining two or more attributes (or objects) into a single attribute (or object)
- Purpose
  - Data reduction
    - ✓ Reduce the number of attributes or objects
  - Change of scale
    - ✓ Cities aggregated into regions, states, countries, etc
  - More “stable” data
    - ✓ Aggregated data tends to have less variability

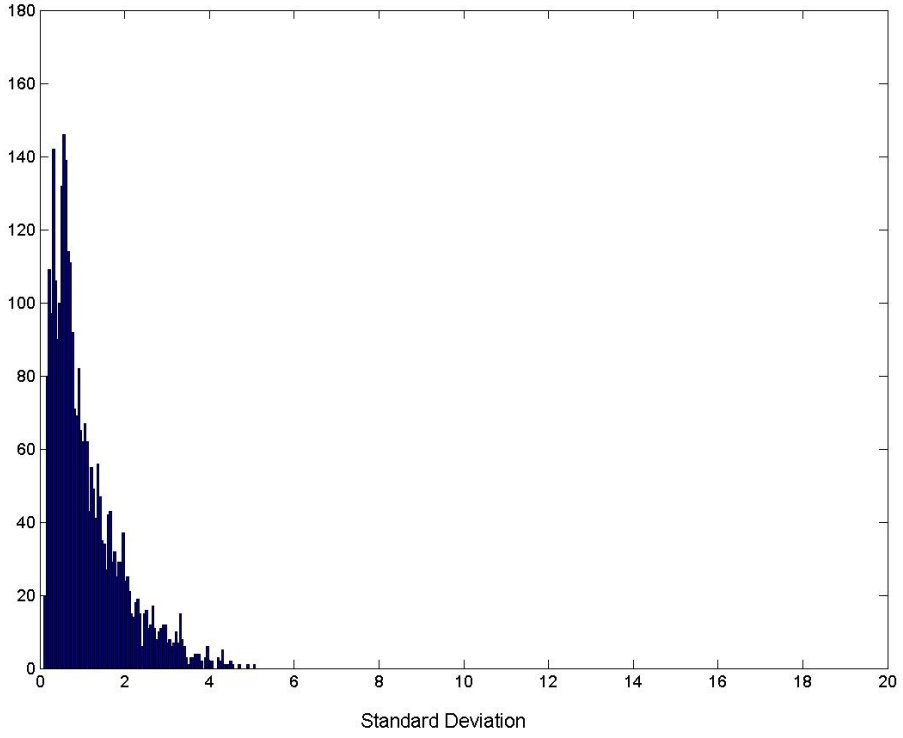
# Aggregation...



- Variation of Precipitation in Australia




Standard Deviation of Average Monthly Precipitation




Standard Deviation of Average Yearly Precipitation

# Sampling



- Sampling is the main technique employed for data selection.
  - It is often used for both the preliminary investigation of the data and the final data analysis.
- Statisticians sample because obtaining the entire set of data of interest is too expensive or time consuming.
- Sampling is used in data mining because processing the entire set of data of interest is too expensive or time consuming.
- The key principle for effective sampling is the following:
  - using a sample will work almost as well as using the entire data sets, if the sample is representative
  - A sample is representative if it has approximately the same property (of interest) as the original set of data

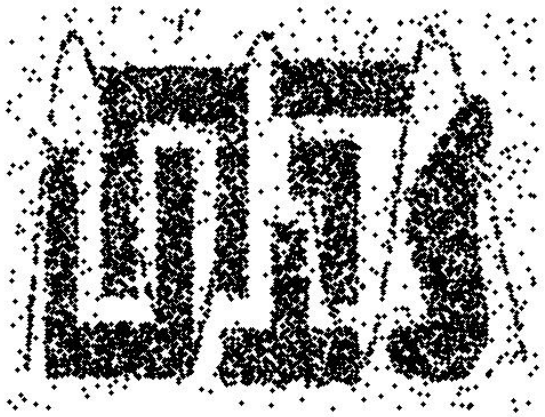
# Types of Sampling



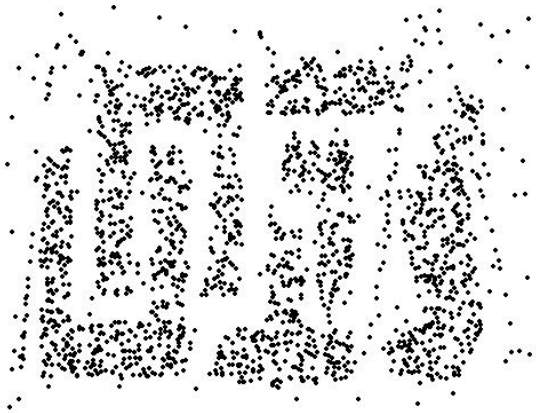
- Simple Random Sampling
  - ✓ There is an equal probability of selecting any particular item
- Sampling without replacement
  - ✓ As each item is selected, it is removed from the population
- Sampling with replacement
  - ✓ Objects are not removed from the population as they are selected for the sample.
  - ✓ In sampling with replacement, the same object can be picked up more than once
- Stratified sampling
  - ✓ Split the data into several partitions; then draw random samples from each partition

# Sample Size

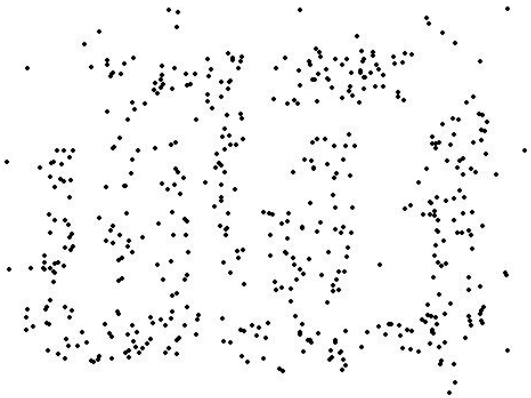




8000 points



2000 Points

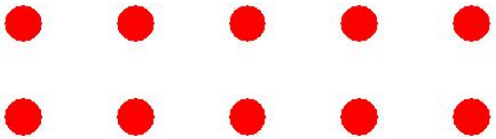


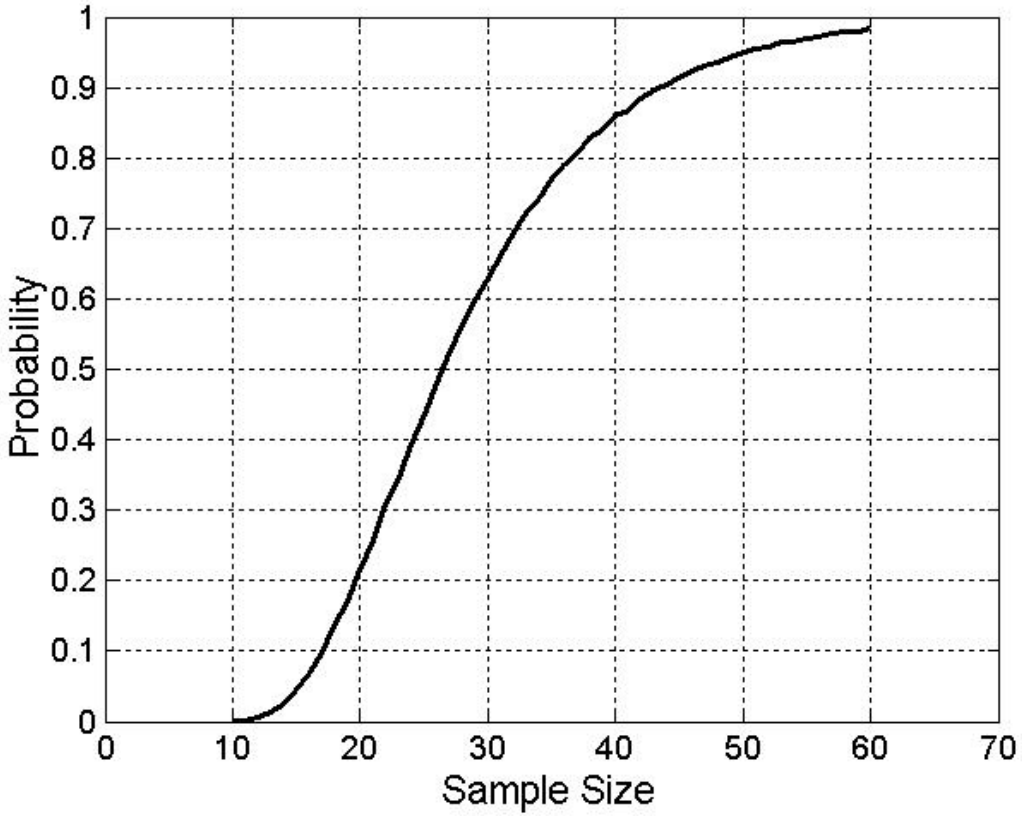
500 Points

# Sample Size



- What sample size is necessary to get at least one object from each of 10 groups.





# Curse of Dimensionality



- When dimensionality increases, data becomes increasingly sparse in the space that it occupies
- Definitions of density and distance between points, which is critical for clustering and outlier detection, become less meaningful

# Dimensionality Reduction

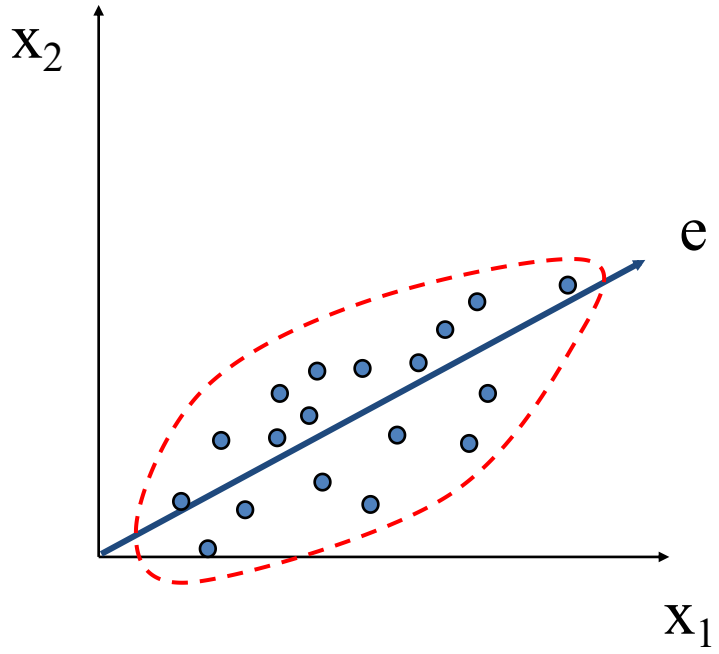


- Purpose:
  - Avoid curse of dimensionality
  - Reduce amount of time and memory required by data mining algorithms
  - Allow data to be more easily visualized
  - May help to eliminate irrelevant features or reduce noise
- Techniques
  - Principle Component Analysis
  - Singular Value Decomposition
  - Others: supervised and non-linear techniques

# Dimensionality Reduction: PCA



- Goal is to find a projection that captures the largest amount of variation in data

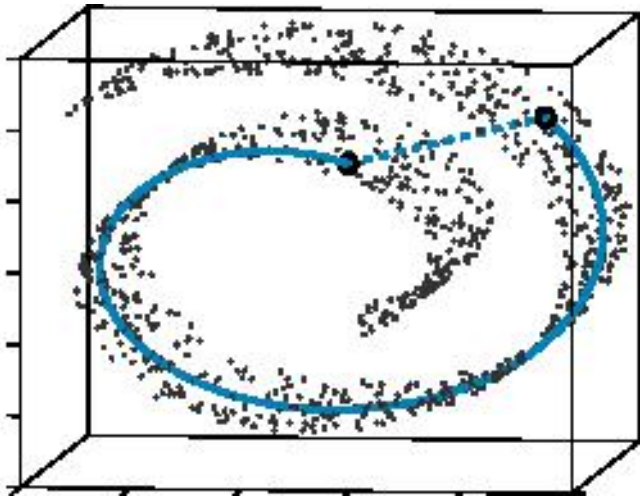



- Find the eigenvectors of the covariance matrix
- The eigenvectors define the new space

# Dimensionality Reduction: ISOMAP



By: Tenenbaum, de Silva,
Langford (2000)



- Construct a neighbourhood graph
- For each pair of points in the graph, compute the shortest path distances – geodesic distances

# Feature Subset Selection



- Another way to reduce dimensionality of data
- Redundant features
  - duplicate much or all of the information contained in one or more other attributes
    - ✓ Example: purchase price of a product and the amount of sales tax paid
- Irrelevant features
  - contain no information that is useful for the data mining task at hand
    - ✓ Example: students' ID is often irrelevant to the task of predicting students' GPA
- Techniques:
  - Brute-force approch: Try all possible feature subsets as input to data mining algorithm
  - Embedded approaches: Feature selection occurs naturally as part of the data mining algorithm
  - Filter approaches: Features are selected before data mining algorithm is run
  - Wrapper approaches: Use the data mining algorithm as a black box to find best subset of attributes

# Feature Creation

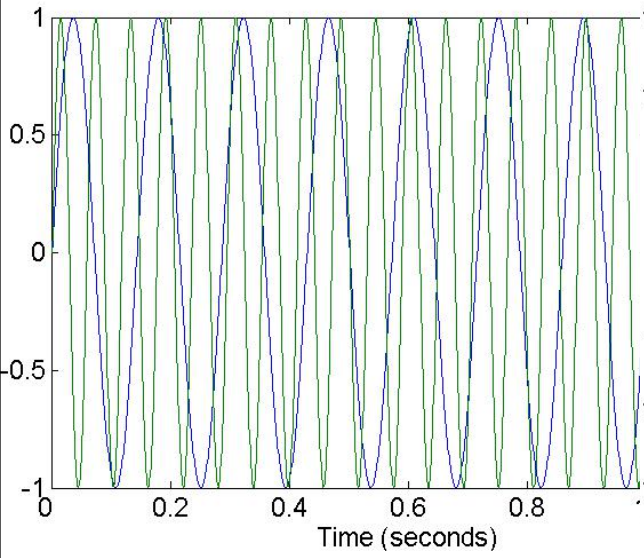


- Create new attributes that can capture the important information in a data set much more efficiently than the original attributes
- Three general methodologies:
  - Feature Extraction
    - ✓ domain-specific
  - Mapping Data to New Space
  - Feature Construction
    - ✓ combining features

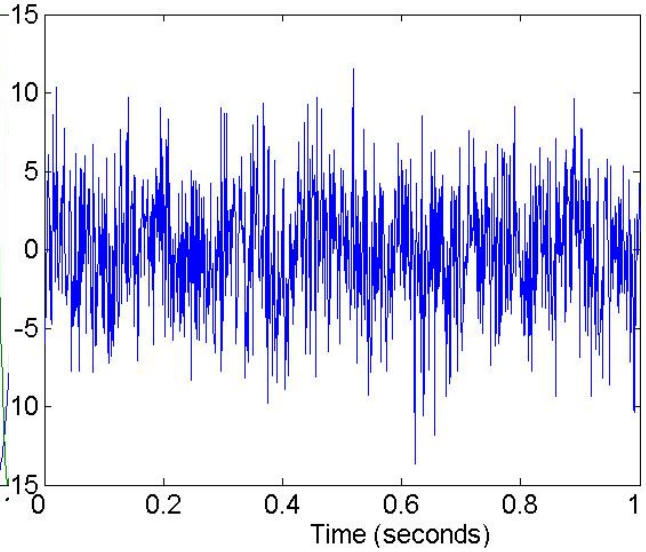
# Mapping Data to a New Space



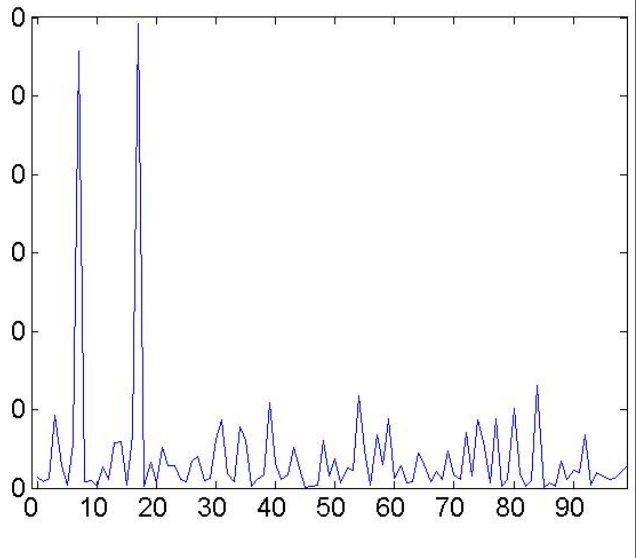
- Fourier transform
- Wavelet transform




Two Sine Waves




Two Sine Waves + Noise

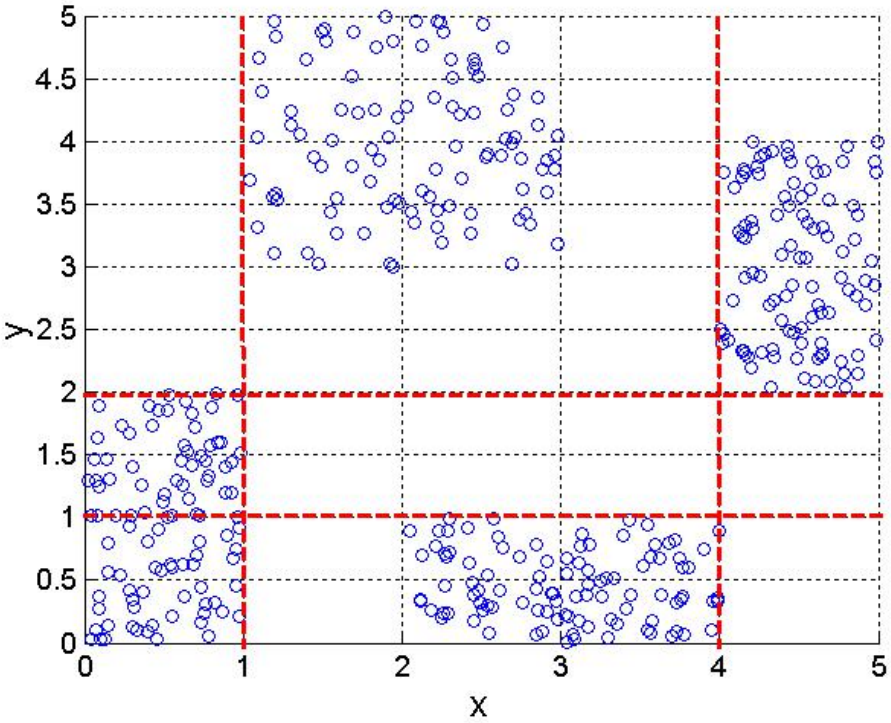



Frequency

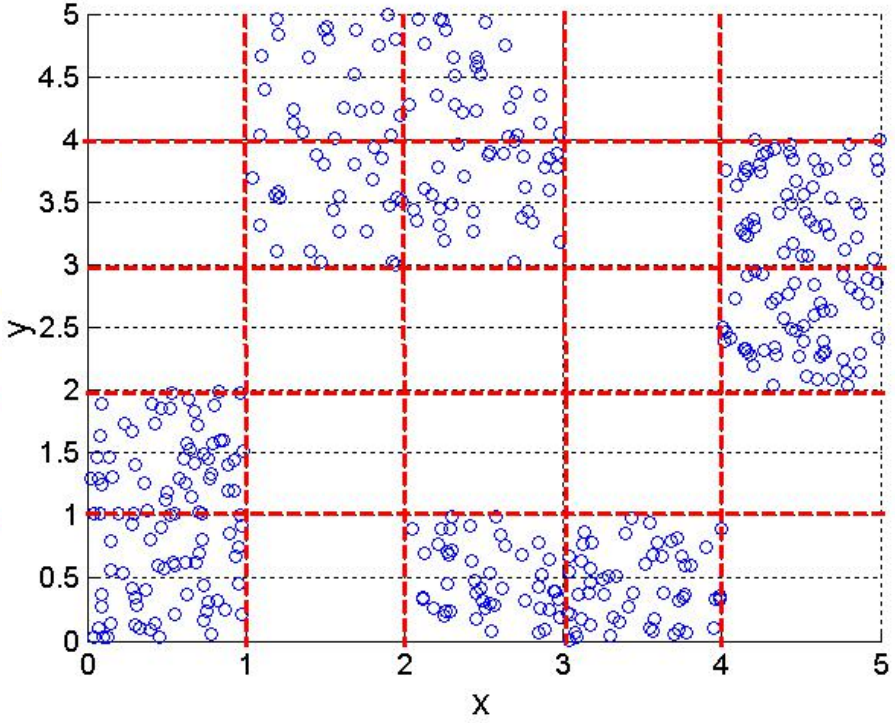
# Discretization Using Class Labels



- Entropy based approach



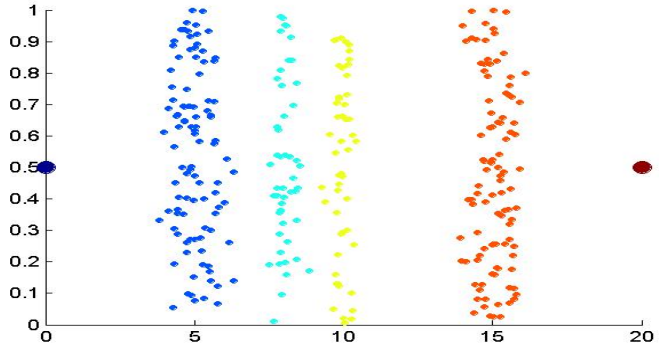

3 categories for both x and y



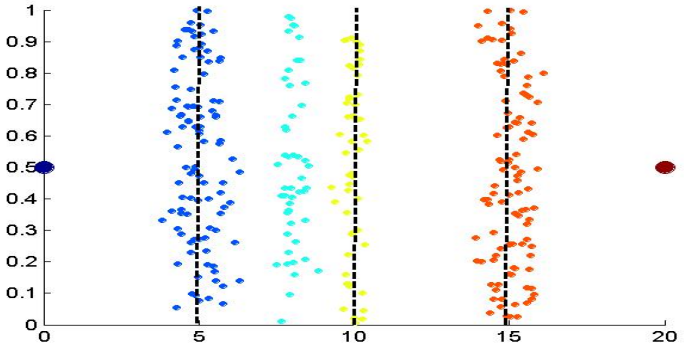

5 categories for both x and y

# Discretization Without Using Class Labels

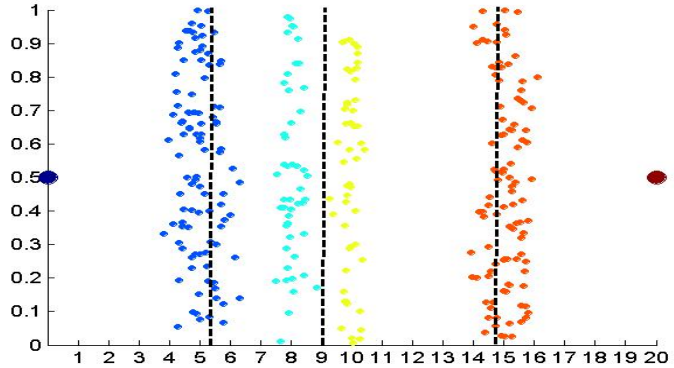




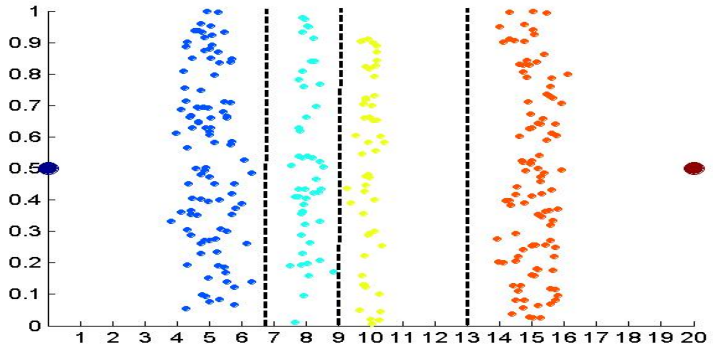

Data




Equal interval




Equal frequency

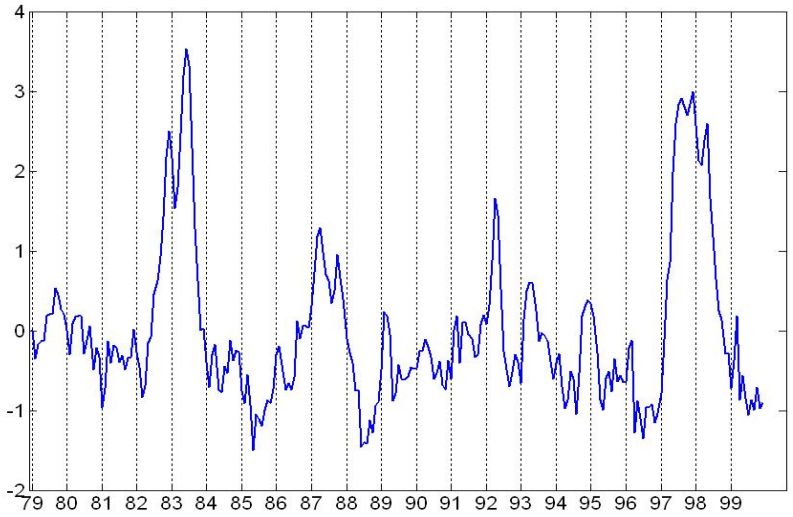



K-means

# Attribute Transformation



- A function that maps the entire set of values of a given attribute to a new set of replacement values such that each old value can be identified with one of the new values
  - Simple functions: $x^k$, log(x), $e^x$, |x|
  - Standardization and Normalization



# Similarity and Dissimilarity



- Similarity
  - Numerical measure of how alike two data objects are.
  - Is higher when objects are more alike.
  - Often falls in the range [0,1]
- Dissimilarity
  - Numerical measure of how different are two data objects
  - Lower when objects are more alike
  - Minimum dissimilarity is often 0
  - Upper limit varies
- Proximity refers to a similarity or dissimilarity

# Similarity/Dissimilarity for Simple Attributes



- p and q are the attribute values for two data objects.

| Attribute Type | Dissimilarity | Similarity |
|---|---|---|
| Nominal | $d = \begin{cases} 0 & \text{if } p = q \\ 1 & \text{if } p \neq q \end{cases}$ | $s = \begin{cases} 1 & \text{if } p = q \\ 0 & \text{if } p \neq q \end{cases}$ |
| Ordinal | $d = \frac{\lvert p-q \rvert}{n-1}$ (values mapped to integers 0 to $n-1$, where $n$ is the number of values) | $s = 1 - \frac{\lvert p-q \rvert}{n-1}$ |
| Interval or Ratio | $d = \lvert p - q \rvert$ | $s = -d$, $s = \frac{1}{1+d}$ or $s = 1 - \frac{d - min\_d}{max\_d - min\_d}$ |

**Table 5.1.** Similarity and dissimilarity for simple attributes

# Euclidean Distance



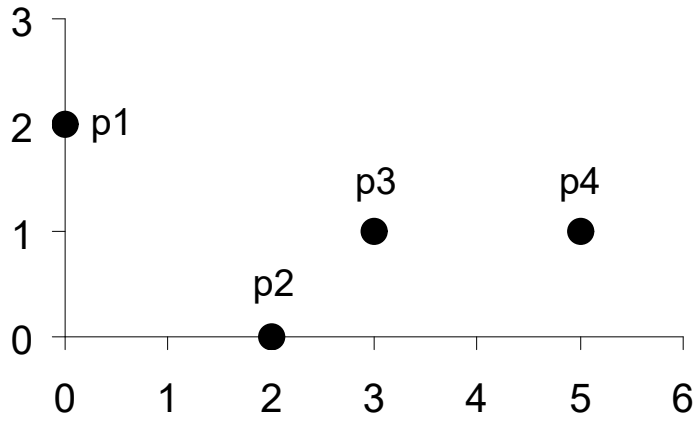
- Euclidean Distance

$$dist = \sqrt{\sum_{k=1}^{n} (p_k - q_k)^2}$$

- Where n is the number of dimensions (attributes) and pk and qk are, respectively, the kth attributes (components) or data objects p and q.
- Standardization is necessary, if scales differ.

# Euclidean Distance






| point | x | y |
|---|---|---|
| p1 | 0 | 2 |
| p2 | 2 | 0 |
| p3 | 3 | 1 |
| p4 | 5 | 1 |

| | p1 | p2 | p3 | p4 |
|---|---|---|---|---|
| p1 | 0 | 2.828 | 3.162 | 5.099 |
| p2 | 2.828 | 0 | 1.414 | 3.162 |
| p3 | 3.162 | 1.414 | 0 | 2 |
| p4 | 5.099 | 3.162 | 2 | 0 |

**Distance Matrix**

# Minkowski Distance



- Minkowski Distance is a generalization of Euclidean Distance

$$dist = \left( \sum_{k=1}^{n} | p_k - q_k |^r \right)^{\frac{1}{r}}$$

- Where r is a parameter, n is the number of dimensions (attributes) and $p_k$ and $q_k$ are, respectively, the kth attributes (components) or data objects p and q.

# Minkowski Distance:Example



- $r = 1$. City block (Manhattan, taxicab, $L_1$ norm) distance.
  A common example of this is the Hamming distance, which is just the number of bits that are different between two binary vectors

- $r = 2$. Euclidean distance

- $r \to \infty$. "supremum" ($L_{max}$ norm, $L_\infty$ norm) distance.
  This is the maximum difference between any component of the vectors

- Do not confuse $r$ with $n$, i.e., all these distances are defined for all numbers of dimensions.

# Minkowski Distance



| point | x | y |
|---|---|---|
| p1 | 0 | 2 |
| p2 | 2 | 0 |
| p3 | 3 | 1 |
| p4 | 5 | 1 |

| L1 | p1 | p2 | p3 | p4 |
|---|---|---|---|---|
| p1 | 0 | 4 | 4 | 6 |
| p2 | 4 | 0 | 2 | 4 |
| p3 | 4 | 2 | 0 | 2 |
| p4 | 6 | 4 | 2 | 0 |

| L2 | p1 | p2 | p3 | p4 |
|---|---|---|---|---|
| p1 | 0 | 2.828 | 3.162 | 5.099 |
| p2 | 2.828 | 0 | 1.414 | 3.162 |
| p3 | 3.162 | 1.414 | 0 | 2 |
| p4 | 5.099 | 3.162 | 2 | 0 |

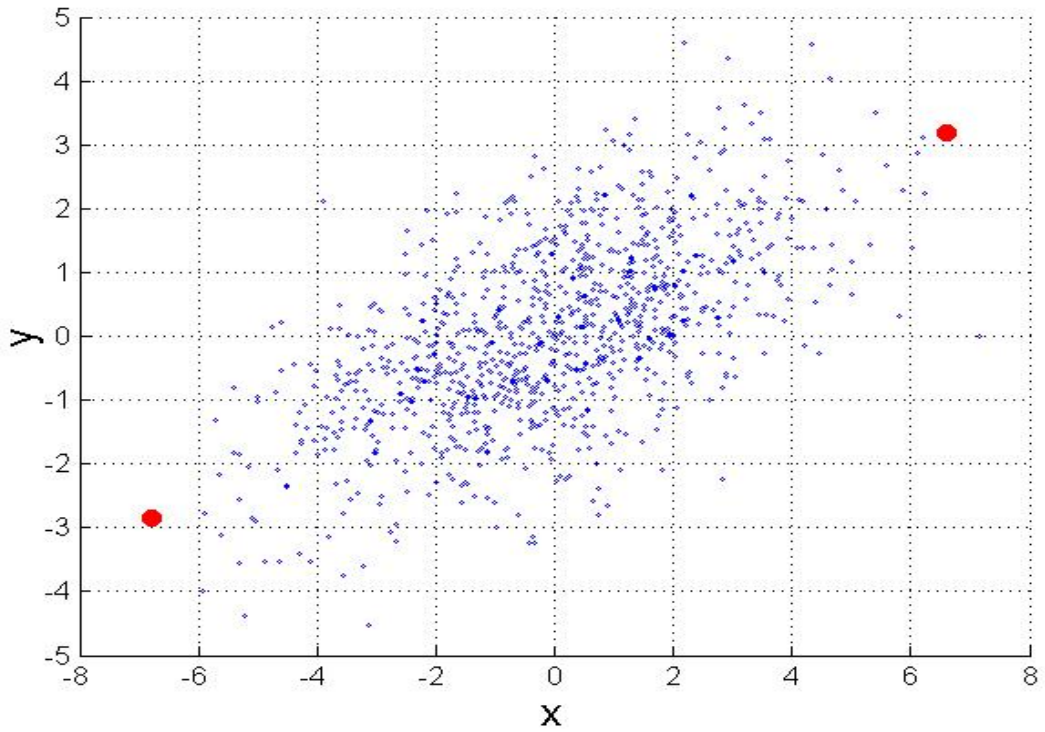
| $L_\infty$ | p1 | p2 | p3 | p4 |
|---|---|---|---|---|
| p1 | 0 | 2 | 3 | 5 |
| p2 | 2 | 0 | 1 | 3 |
| p3 | 3 | 1 | 0 | 2 |
| p4 | 5 | 3 | 2 | 0 |

Distance Matrix

# Mahalanobis Distance



$$mahalanobis(p,q) = (p-q)\Sigma^{-1}(p-q)^T$$



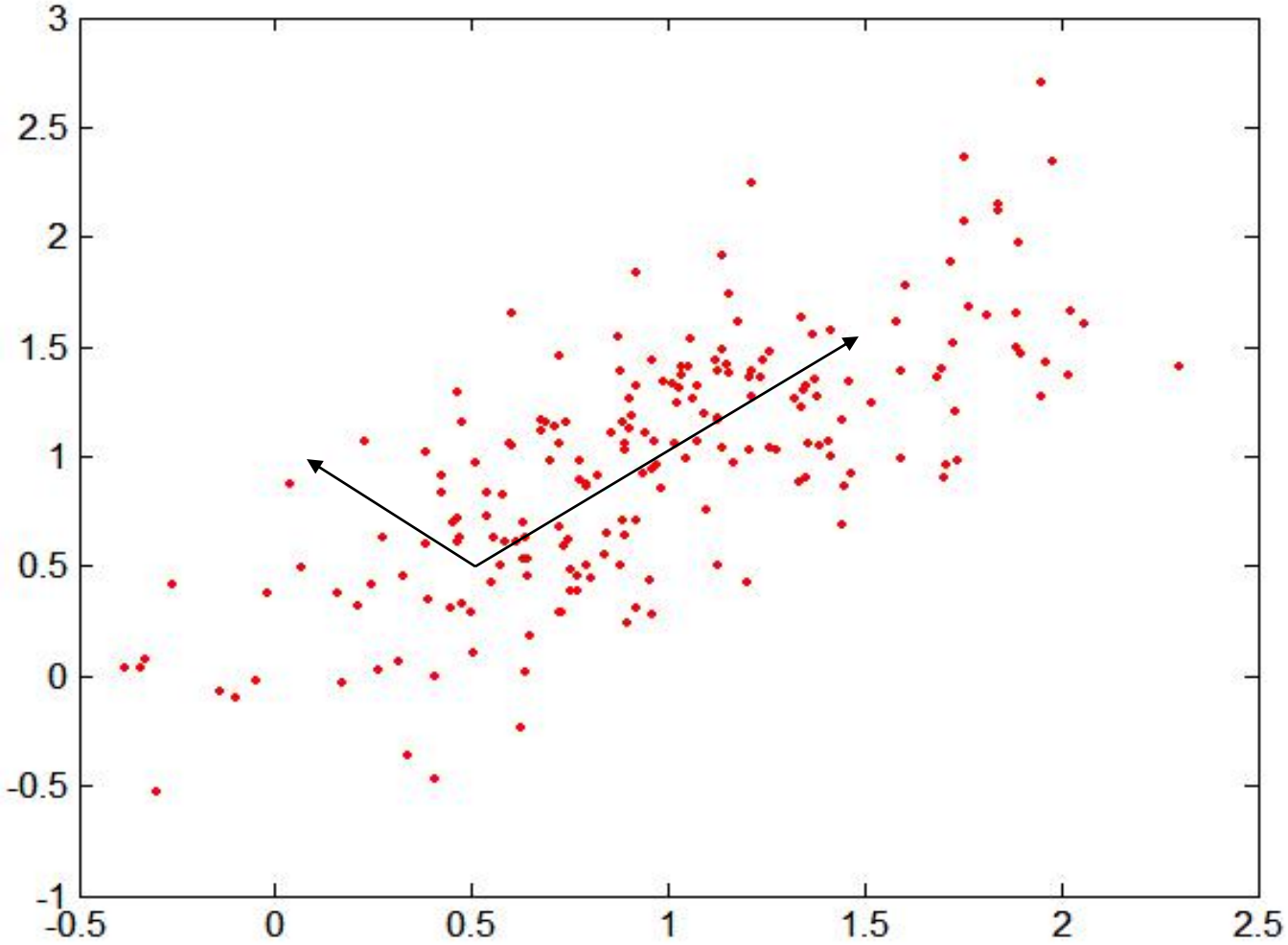

$\Sigma$ is the covariance matrix of the input data $X$

$$\Sigma_{j,k} = \frac{1}{n-1}\sum_{i=1}^{n}(X_{ij} - \overline{X}_j)(X_{ik} - \overline{X}_k)$$

For red points, the Euclidean distance is 14.7, Mahalanobis distance is 6.

# Mahalanobis Distance






Covariance Matrix:

$$\Sigma = \begin{bmatrix} 0.3 & 0.2 \\ 0.2 & 0.3 \end{bmatrix}$$

A: (0.5, 0.5)

B: (0, 1)

C: (1.5, 1.5)

Mahal(A,B) = 5

Mahal(A,C) = 4

# Common Properties of a Distance



- Distances, such as the Euclidean distance, have some well known properties.

1. $d(p, q) \geq 0$ for all $p$ and $q$ and $d(p, q) = 0$ only if $p = q$. (Positive definiteness)
2. $d(p, q) = d(q, p)$ for all $p$ and $q$. (Symmetry)
3. $d(p, r) \leq d(p, q) + d(q, r)$ for all points $p$, $q$, and $r$. (Triangle Inequality)

- where $d(p, q)$ is the distance (dissimilarity) between points (data objects), $p$ and $q$.
- A distance that satisfies these properties is a metric

# Similarity Between Binary Vectors



- Common situation is that objects, *p* and *q*, have only binary attributes

- Compute similarities using the following quantities

  $M_{01}$ = the number of attributes where p was 0 and q was 1

  $M_{10}$ = the number of attributes where p was 1 and q was 0

  $M_{00}$ = the number of attributes where p was 0 and q was 0

  $M_{11}$ = the number of attributes where p was 1 and q was 1

- Simple Matching and Jaccard Coefficients

  SMC = number of matches / number of attributes

  $= (M_{11} + M_{00}) / (M_{01} + M_{10} + M_{11} + M_{00})$

  J = number of 11 matches / number of not-both-zero attributes values

  $= (M_{11}) / (M_{01} + M_{10} + M_{11})$

# SMC versus Jaccard: Example



$p$ = 1 0 0 0 0 0 0 0 0 0

$q$ = 0 0 0 0 0 0 1 0 0 1

$M_{01} = 2$ (the number of attributes where p was 0 and q was 1)

$M_{10} = 1$ (the number of attributes where p was 1 and q was 0)

$M_{00} = 7$ (the number of attributes where p was 0 and q was 0)

$M_{11} = 0$ (the number of attributes where p was 1 and q was 1)

$SMC = (M_{11} + M_{00})/(M_{01} + M_{10} + M_{11} + M_{00}) = (0+7) / (2+1+0+7) = 0.7$

$J = (M_{11}) / (M_{01} + M_{10} + M_{11}) = 0 / (2 + 1 + 0) = 0$

# Cosine Similarity



- If $d_1$ and $d_2$ are two document vectors, then

$$\cos(d_1, d_2) = (d_1 \bullet d_2) / \|d_1\| \|d_2\| ,$$

where $\bullet$ indicates vector dot product and $\| d \|$ is the length of vector $d$.

- Example:

$d_1 =$ **3 2 0 5 0 0 0 2 0 0**
$d_2 =$ **1 0 0 0 0 0 0 1 0 2**

$d_1 \bullet d_2 = 3*1 + 2*0 + 0*0 + 5*0 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2 = 5$

$\|d_1\| = (3*3+2*2+0*0+5*5+0*0+0*0+0*0+2*2+0*0+0*0)^{0.5} = (42)^{0.5} = 6.481$

$\|d_2\| = (1*1+0*0+0*0+0*0+0*0+0*0+0*0+1*1+0*0+2*2)^{0.5} = (6)^{0.5} = 2.245$

$\cos(d_1, d_2) = .3150$

# Recommended Text and Reference Books



- **Text Book:**
  - J. Han and M. Kamber. Data Mining: Concepts and Techniques. Morgan Kaufmann, 3rd ed., 2011
- **Reference Books:**
  - H. Dunham. Data Mining: Introductory and Advanced Topics. Pearson Education. 2006.
  - I. H. Witten and E. Frank. Data Mining: Practical Machine Learning Tools and Techniques. Morgan Kaufmann. 2000.
  - D. Hand, H. Mannila and P. Smyth. Principles of Data Mining.Prentice-Hall. 2001.

# THANK YOU!