CS 501: Data Mining

Introduction to Data Mining

Outline

- Motivation: Why data mining?
- What is data mining?
- Data Mining: On what kind of data?
- Data mining tasks
- Top-10 most popular data mining algorithms
- Major issues in data mining

Why Data Mining?

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

Evolution of Sciences

- Before 1600, **empirical science**
- 1600-1950s, **theoretical science**
  - Each discipline has grown a *theoretical* component. Theoretical models often motivate experiments and generalize our understanding
- 1950s-1990s, **computational science**
  - Over the last 50 years, most disciplines have grown a third, *computational* branch (e.g. empirical, theoretical, and computational ecology, or physics, or linguistics)
  - Computational Science traditionally meant simulation. It grew out of our inability to find closed-form solutions for complex mathematical models
- 1990-now, **data science**
  - The flood of data from new scientific instruments and simulations
  - The ability to economically store and manage petabytes of data online
  - The Internet and computing Grid that makes all these archives universally accessible
  - Scientific info. management, acquisition, organization, query, and visualization tasks scale almost linearly with data volumes. Data mining is a major new challenge!

Jim Gray and Alex Szalay, *The World Wide Telescope: An Archetype for Online Science*, Comm. ACM, 45(11): 50-54, Nov. 2002

Evolution of Database Technology

- 1960s:
  - Data collection, database creation, IMS and network DBMS
- 1970s:
  - Relational data model, relational DBMS implementation
- 1980s:
  - RDBMS, advanced data models (extended-relational, OO, deductive, etc.)
  - Application-oriented DBMS (spatial, scientific, engineering, etc.)
- 1990s:
  - Data mining, data warehousing, multimedia databases, and Web databases
- 2000s
  - Stream data management and mining
  - Data mining and its applications
  - Web technology (XML, data integration) and global information systems

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.

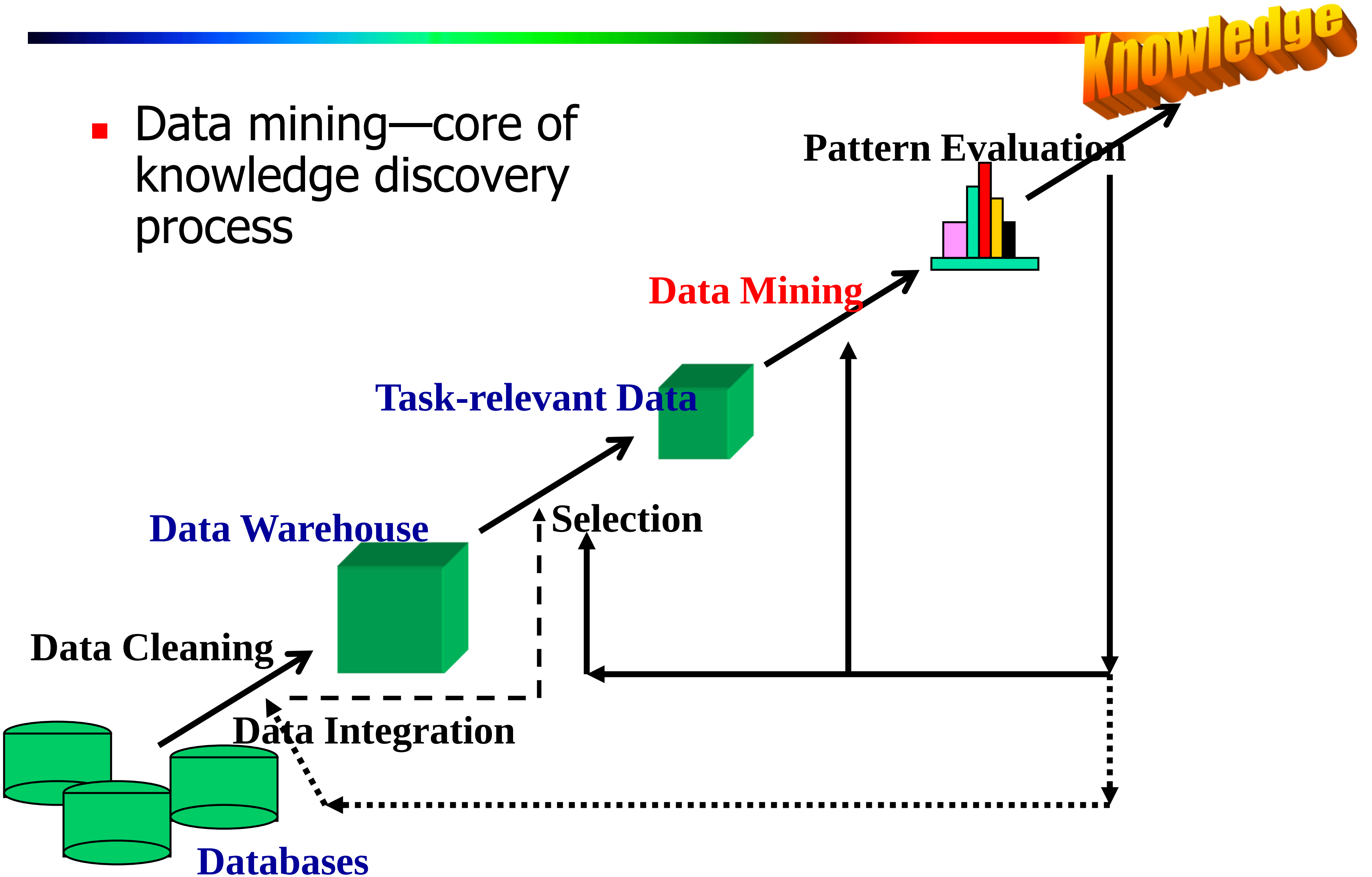
What is (not) Data Mining?

- What is not Data Mining?
  - Look up phone number in phone directory
  - Query a Web search engine for information about "Amazon"

- 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

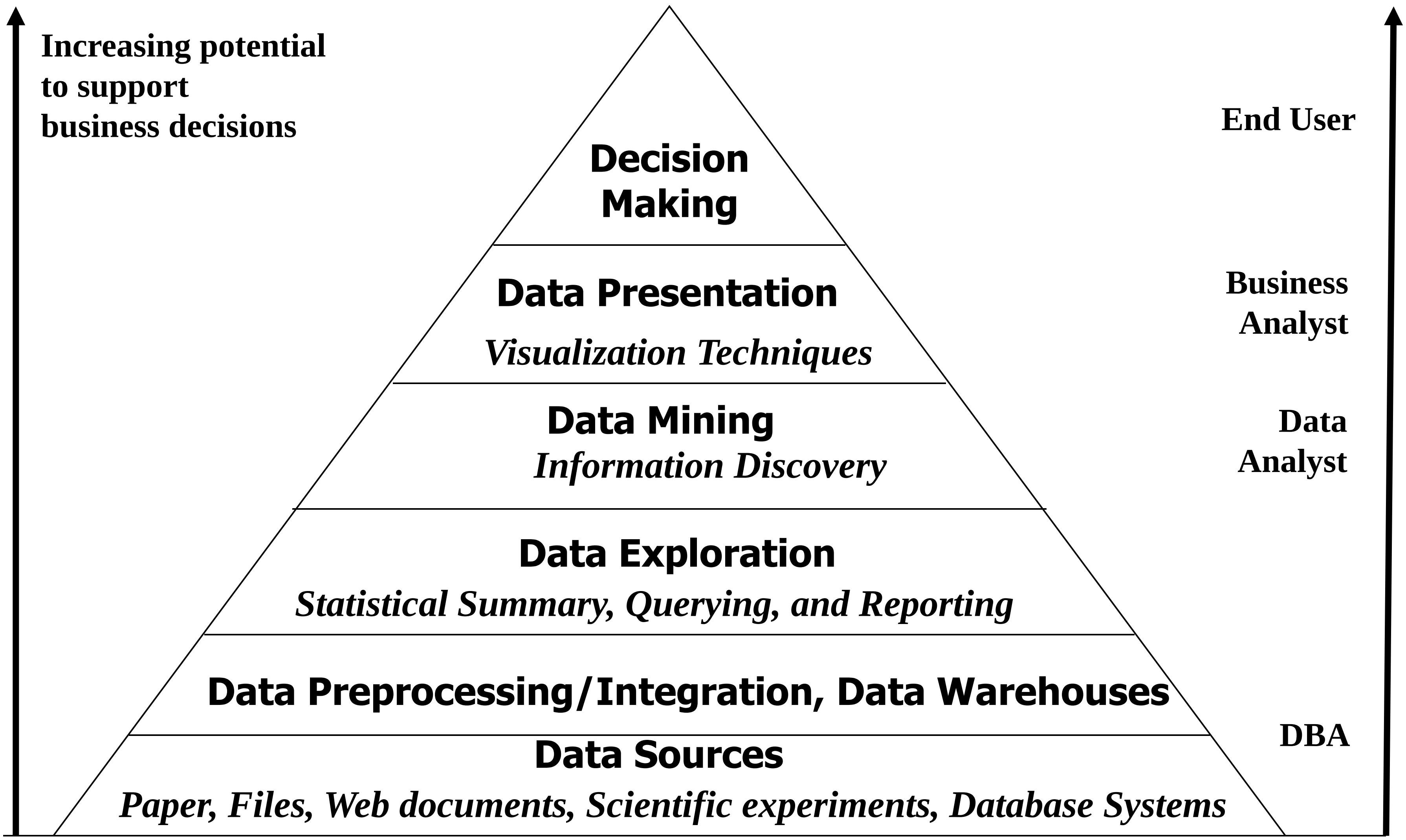
- Data mining—core of knowledge discovery process



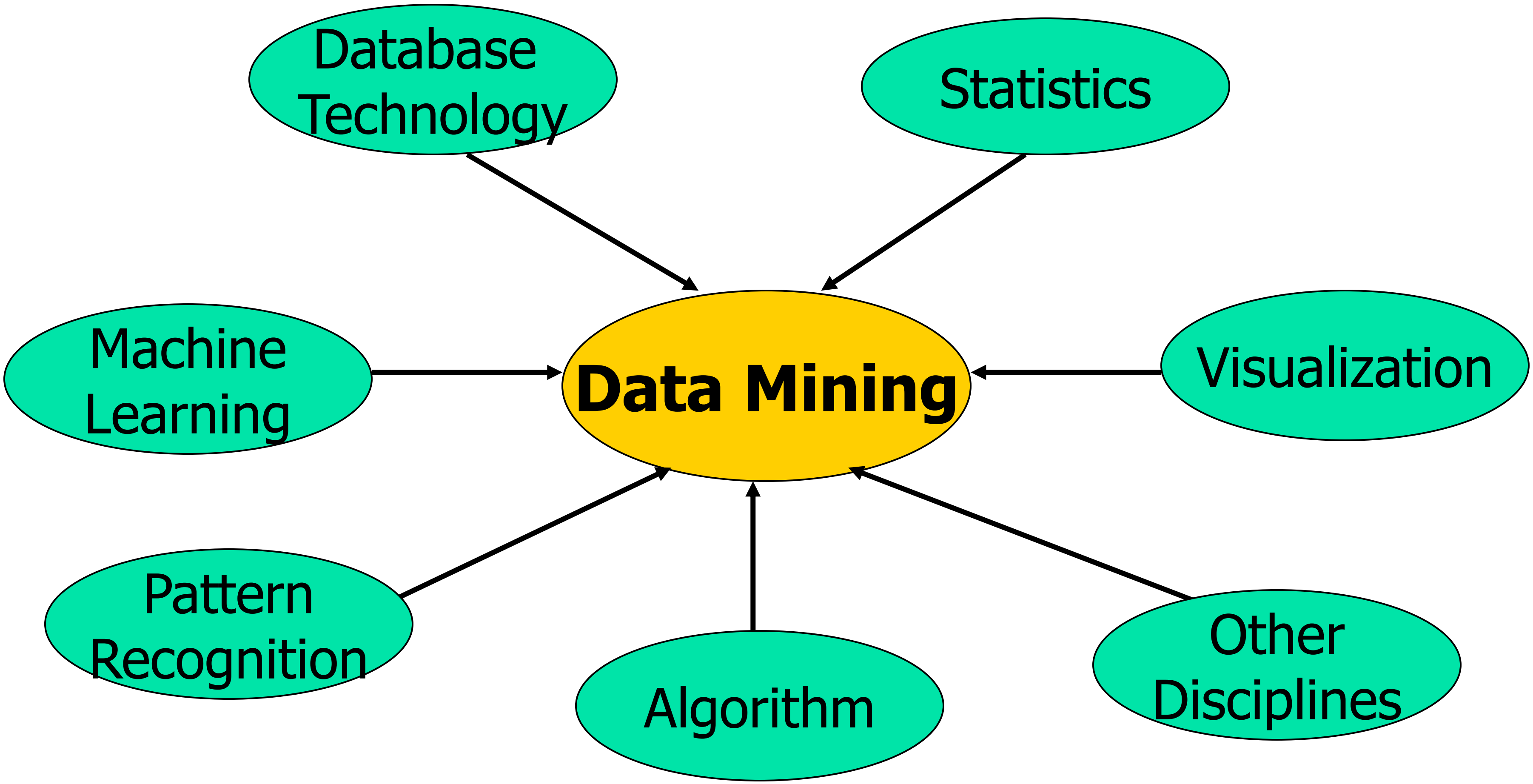
KDD Process: Several Key Steps

- Learning the application domain
  - relevant prior knowledge and goals of application
- Creating a target data set: data selection
- Data cleaning and preprocessing: (may take 60% of effort!)
- Data reduction and transformation
  - Find useful features, dimensionality/variable reduction, invariant representation
- Choosing functions of data mining
  - summarization, classification, regression, association, clustering
- Choosing the mining algorithm(s)
- Data mining: search for patterns of interest
- Pattern evaluation and knowledge presentation
  - visualization, transformation, removing redundant patterns, etc.
- Use of discovered knowledge

Data Mining and Business Intelligence



Data Mining: Confluence of Multiple Disciplines



Why Not Traditional Data Analysis?

- 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
  - Temporal data, sequence data
  - Structure data, graphs, social networks and multi-linked data
  - Heterogeneous databases
  - Spatial, spatiotemporal, multimedia, text and Web data
  - Software programs, scientific simulations
- New and sophisticated applications

Multi-Dimensional View of Data Mining

- **<u>Data to be mined</u>**
  - Relational, data warehouse, transactional, stream, object-oriented/relational, active, spatial, time-series, text, multi-media, heterogeneous, WWW
- **<u>Knowledge to be mined</u>**
  - Characterization, discrimination, association, classification, clustering, trend/deviation, outlier analysis, etc.
  - Multiple/integrated functions and mining at multiple levels
- **<u>Techniques utilized</u>**
  - Database-oriented, data warehouse (OLAP), machine learning, statistics, visualization, etc.
- **<u>Applications adapted</u>**
  - 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
  - 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

- Description Methods
  - Find human-interpretable patterns that describe the data

From [Fayyad, et.al.] Advances in Knowledge Discovery and Data Mining, 1996

Data Mining Tasks...

- Classification [Predictive]
- Clustering [Descriptive]
- Association Rule Discovery [Descriptive]
- Sequential Pattern Discovery [Descriptive]
- Regression [Predictive]
- Deviation Detection [Predictive]

Classification: Definition

- Given a collection of records (*training set*)
  - Each record contains a set of *attributes/ features*, one of the attributes is the *class*
- Find a *model* for class attribute as a function of the values of other attributes

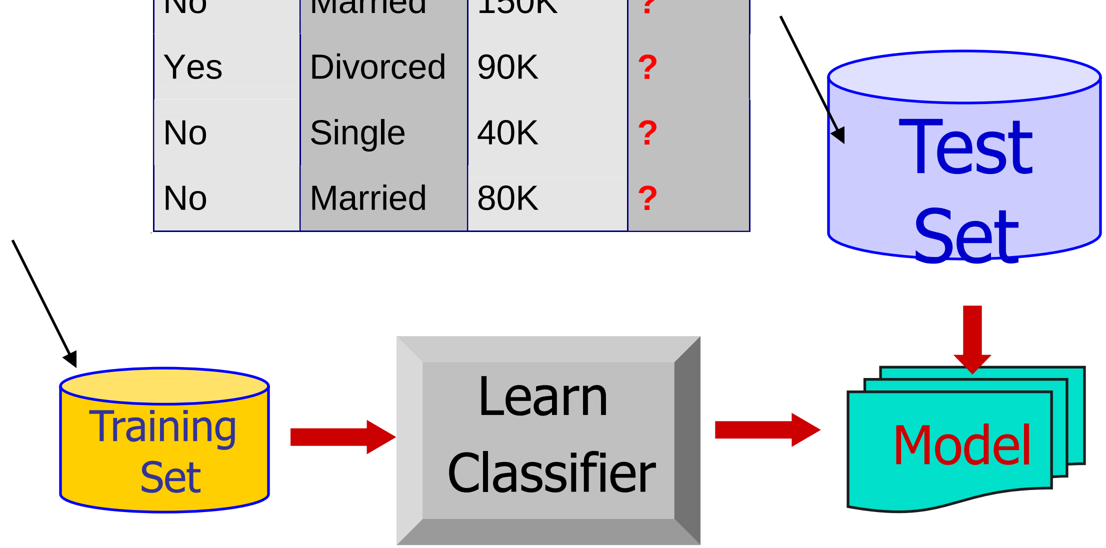
- Goal: <u>Previously unseen</u> records should be assigned a class as accurately as possible
  - A *test set* is used to determine the accuracy of the model. Usually, the given data set is divided into training and test sets, with training set used to build the model and test set used to validate it

Classification Example

categorical categorical continuous class

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**

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



Classification: Application 1

- Direct Marketing
  - Goal: Reduce cost of mailing by *targeting* a set of consumers likely to buy a new cell-phone product
  - Approach:
    - Use the data for a similar product introduced before
    - We know which customers decided to buy and which decided otherwise. This *{buy, don't buy}* decision forms the *class attribute*
    - Collect various demographic, lifestyle, and company-interaction related information about all such customers
      - Type of business, where they stay, how much they earn, etc
    - Use this information as input attributes to learn a classifier model

From [Berry & Linoff] Data Mining Techniques, 1997

Classification: Application 2

- Fraud Detection
  - Goal: Predict fraudulent cases in credit card transactions
  - Approach:
    - Use credit card transactions and the information on its account-holder as attributes
      - When does a customer buy? what does he buy? how often he pays on time? etc.
    - Label past transactions as *fraud* or *fair* transactions
    - Learn a model for the class of the transactions
    - Use this model to detect fraud by observing credit card transactions on an account

Clustering Definition

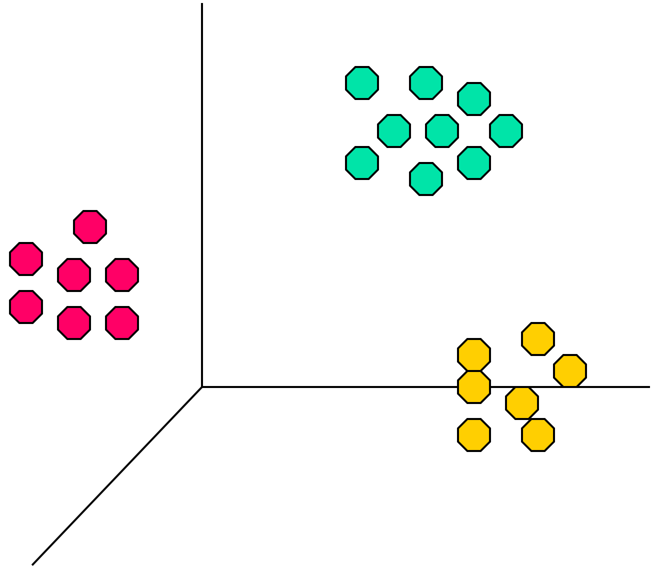
- Given a set of data points, each having a set of attributes, and a similarity measure among them, find clusters such that
  - Data points in one cluster are more similar to one another
  - Data points in separate clusters are less similar to one another
- Similarity Measures:
  - Euclidean Distance if attributes are continuous
  - Other Problem-specific Measures

Illustrating Clustering

- Euclidean Distance Based Clustering in 3-D space

Intracluster distances are minimized

Intercluster distances are maximized



Clustering: Application

- Document Clustering:
  - Goal: To find groups of documents that are similar to each other based on the important terms appearing in them
  - Approach: Identify frequently occurring terms in each document. Form a similarity measure based on the frequencies of different terms. Use it to cluster
  - Gain: Information Retrieval can utilize the clusters to relate a new document or search term to clustered documents

Association Rule Discovery: Definition

- Given a set of records each of which contains some number of items from a given collection
  - Produce dependency rules which will predict occurrence of an item based on occurrences of other items

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}

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 advertising expenditure
  - Predicting wind velocities as a function of temperature, humidity, air pressure, etc.
  - Time series prediction of stock market indices

Top-10 Most Popular DM Algorithms: 18 Identified Candidates (I)

- Classification
  - #1. C4.5: Quinlan, J. R. C4.5: Programs for Machine Learning. Morgan Kaufmann., 1993.
  - #2. CART: L. Breiman, J. Friedman, R. Olshen, and C. Stone. Classification and Regression Trees. Wadsworth, 1984.
  - #3. K Nearest Neighbours (kNN): Hastie, T. and Tibshirani, R. 1996. Discriminant Adaptive Nearest Neighbor Classification. TPAMI. 18(6)
  - #4. Naive Bayes Hand, D.J., Yu, K., 2001. Idiot's Bayes: Not So Stupid After All? Internat. Statist. Rev. 69, 385-398.
- Statistical Learning
  - #5. SVM: Vapnik, V. N. 1995. The Nature of Statistical Learning Theory. Springer-Verlag.
  - #6. EM: McLachlan, G. and Peel, D. (2000). Finite Mixture Models. J. Wiley, New York. Association Analysis
  - #7. Apriori: Rakesh Agrawal and Ramakrishnan Srikant. Fast Algorithms for Mining Association Rules. In VLDB '94.
  - #8. FP-Tree: Han, J., Pei, J., and Yin, Y. 2000. Mining frequent patterns without candidate generation. In SIGMOD '00.

The 18 Identified Candidates (II)

- Link Mining
  - #9. PageRank: Brin, S. and Page, L. 1998. The anatomy of a large-scale hypertextual Web search engine. In WWW-7, 1998.
  - #10. HITS: Kleinberg, J. M. 1998. Authoritative sources in a hyperlinked environment. SODA, 1998.
- Clustering
  - #11. K-Means: MacQueen, J. B., Some methods for classification and analysis of multivariate observations, in Proc. 5th Berkeley Symp. Mathematical Statistics and Probability, 1967.
  - #12. BIRCH: Zhang, T., Ramakrishnan, R., and Livny, M. 1996. BIRCH: an efficient data clustering method for very large databases. In SIGMOD '96.
- Bagging and Boosting
  - #13. AdaBoost: Freund, Y. and Schapire, R. E. 1997. A decision-theoretic generalization of on-line learning and an application to boosting. J. Comput. Syst. Sci. 55, 1 (Aug. 1997), 119-139.

The 18 Identified Candidates (III)

- Sequential Patterns
  - #14. GSP: Srikant, R. and Agrawal, R. 1996. Mining Sequential Patterns: Generalizations and Performance Improvements. In Proceedings of the 5th International Conference on Extending Database Technology, 1996.
  - #15. PrefixSpan: J. Pei, J. Han, B. Mortazavi-Asl, H. Pinto, Q. Chen, U. Dayal and M-C. Hsu. PrefixSpan: Mining Sequential Patterns Efficiently by Prefix-Projected Pattern Growth. In ICDE '01.
- Integrated Mining
  - #16. CBA: Liu, B., Hsu, W. and Ma, Y. M. Integrating classification and association rule mining. KDD-98.
- Rough Sets
  - #17. Finding reduct: Zdzislaw Pawlak, Rough Sets: Theoretical Aspects of Reasoning about Data, Kluwer Academic Publishers, Norwell, MA, 1992
- Graph Mining
  - #18. gSpan: Yan, X. and Han, J. 2002. gSpan: Graph-Based Substructure Pattern Mining. In ICDM '02.

Top-10 Algorithm Finally Selected at ICDM'06

- **#1: C4.5 (61 votes)**
- **#2: K-Means (60 votes)**
- **#3: SVM (58 votes)**
- **#4: Apriori (52 votes)**
- **#5: EM (48 votes)**
- **#6: PageRank (46 votes)**
- **#7: AdaBoost (45 votes)**
- **#7: kNN (45 votes)**
- **#7: Naive Bayes (45 votes)**
- **#10: CART (34 votes)**

Major Issues in Data Mining

- <u>Mining methodology</u>
  - Mining different kinds of knowledge from diverse data types, e.g., bio, stream, Web
  - Performance: efficiency, effectiveness, and scalability
  - Pattern evaluation: the interestingness problem
  - Incorporation of background knowledge
  - Handling noise and incomplete data
  - Parallel, distributed and incremental mining methods
  - Integration of the discovered knowledge with existing one: knowledge fusion
- <u>User interaction</u>
  - Data mining query languages and ad-hoc mining
  - Expression and visualization of data mining results
  - Interactive mining of knowledge at multiple levels of abstraction
- <u>Applications and social impacts</u>
  - Domain-specific data mining & invisible data mining
  - Protection of data security, integrity, and privacy

A Brief History of Data Mining Society

- 1989 IJCAI Workshop on Knowledge Discovery in Databases
  - Knowledge Discovery in Databases (G. Piatetsky-Shapiro and W. Frawley, 1991)
- 1991-1994 Workshops on Knowledge Discovery in Databases
  - Advances in Knowledge Discovery and Data Mining (U. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy, 1996)
- 1995-1998 International Conferences on Knowledge Discovery in Databases and Data Mining (KDD'95-98)
  - Journal of Data Mining and Knowledge Discovery (1997)
- ACM SIGKDD conferences since 1998 and SIGKDD Explorations
- More conferences on data mining
  - PAKDD (1997), PKDD (1997), SIAM-Data Mining (2001), (IEEE) ICDM (2001), etc.
- ACM Transactions on KDD starting in 2007

Conferences and Journals on Data Mining

- KDD Conferences
  - ACM SIGKDD Int. Conf. on Knowledge Discovery in Databases and Data Mining (KDD)
  - SIAM Data Mining Conf. (SDM)
  - (IEEE) Int. Conf. on Data Mining (ICDM)
  - Conf. on Principles and practices of Knowledge Discovery and Data Mining (PKDD)
  - Pacific-Asia Conf. on Knowledge Discovery and Data Mining (PAKDD)
- Other related conferences
  - ACM SIGMOD
  - VLDB
  - (IEEE) ICDE
  - WWW, SIGIR
  - ICML, CVPR, NIPS
- Journals
  - Data Mining and Knowledge Discovery (DAMI or DMKD)
  - IEEE Trans. On Knowledge and Data Eng. (TKDE)
  - KDD Explorations
  - ACM Trans. on KDD

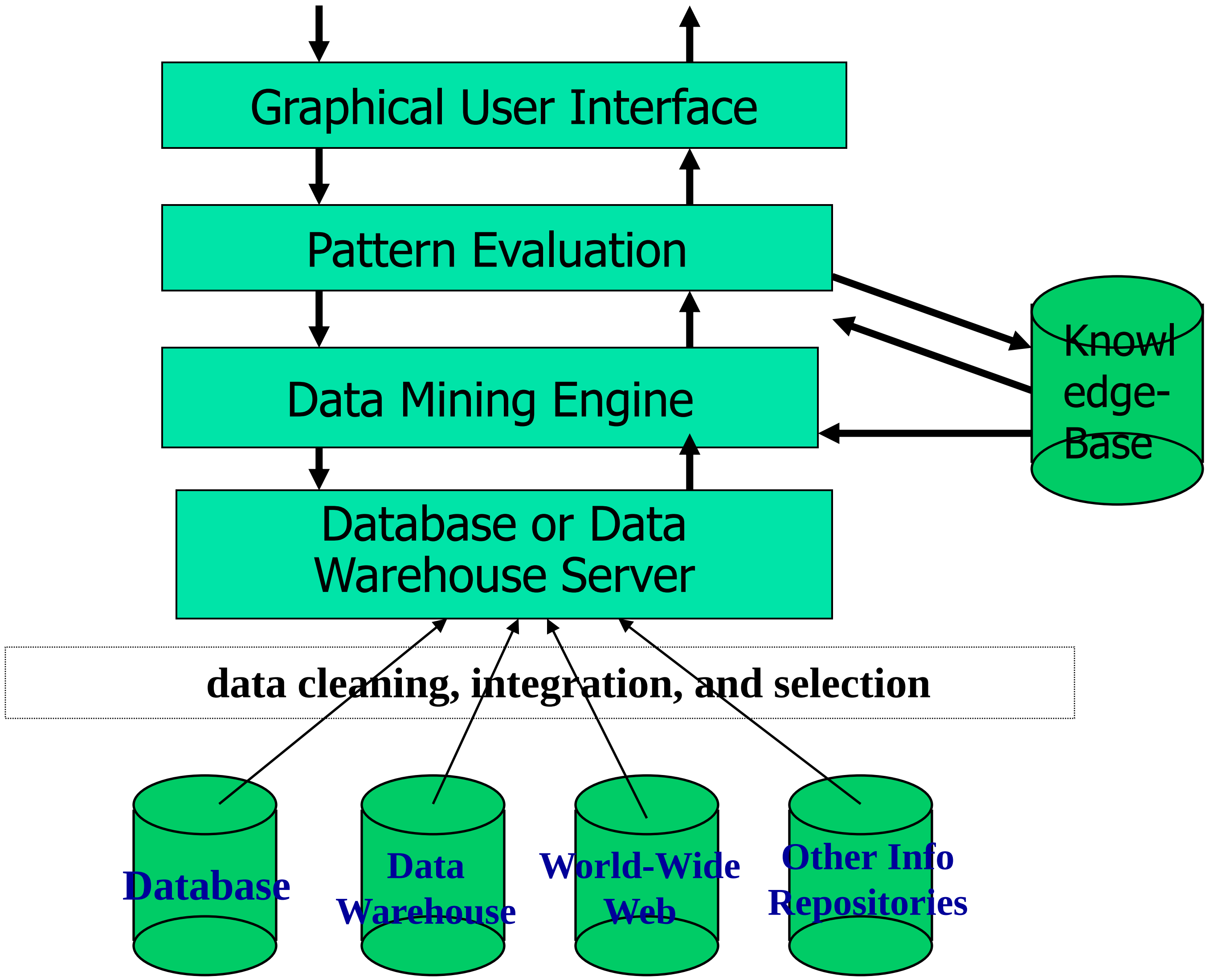
Where to Find References? DBLP, CiteSeer, Google

- Data mining and KDD (SIGKDD: CDROM)
  - Conferences: ACM-SIGKDD, IEEE-ICDM, SIAM-DM, PKDD, PAKDD, etc.
  - Journal: Data Mining and Knowledge Discovery, KDD Explorations, ACM TKDD
- Database systems (SIGMOD: ACM SIGMOD Anthology—CD ROM)
  - Conferences: ACM-SIGMOD, ACM-PODS, VLDB, IEEE-ICDE, EDBT, ICDT, DASFAA
  - Journals: IEEE-TKDE, ACM-TODS/TOIS, JIIS, J. ACM, VLDB J., Info. Sys., etc.
- AI & Machine Learning
  - Conferences: Machine learning (ML), AAAI, IJCAI, COLT (Learning Theory), CVPR, NIPS, etc.
  - Journals: Machine Learning, Artificial Intelligence, Knowledge and Information Systems, IEEE-PAMI, etc.
- Web and IR
  - Conferences: SIGIR, WWW, CIKM, etc.
  - Journals: WWW: Internet and Web Information Systems,
- Statistics
  - Conferences: Joint Stat. Meeting, etc.
  - Journals: Annals of statistics, etc.
- Visualization
  - Conference proceedings: CHI, ACM-SIGGraph, etc.
  - Journals: IEEE Trans. visualization and computer graphics, etc.

Recommended Reference Books

- S. Chakrabarti. Mining the Web: Statistical Analysis of Hypertex and Semi-Structured Data. Morgan Kaufmann, 2002
- R. O. Duda, P. E. Hart, and D. G. Stork, Pattern Classification, 2ed., Wiley-Interscience, 2000
- T. Dasu and T. Johnson. Exploratory Data Mining and Data Cleaning. John Wiley & Sons, 2003
- U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy. Advances in Knowledge Discovery and Data Mining. AAAI/MIT Press, 1996
- U. Fayyad, G. Grinstein, and A. Wierse, Information Visualization in Data Mining and Knowledge Discovery, Morgan Kaufmann, 2001
- J. Han and M. Kamber. Data Mining: Concepts and Techniques. Morgan Kaufmann, 2nd ed., 2006
- D. J. Hand, H. Mannila, and P. Smyth, Principles of Data Mining, MIT Press, 2001
- T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer-Verlag, 2001
- B. Liu, Web Data Mining, Springer 2006.
- T. M. Mitchell, Machine Learning, McGraw Hill, 1997
- G. Piatetsky-Shapiro and W. J. Frawley. Knowledge Discovery in Databases. AAAI/MIT Press, 1991
- P.-N. Tan, M. Steinbach and V. Kumar, Introduction to Data Mining, Wiley, 2005
- S. M. Weiss and N. Indurkhya, Predictive Data Mining, Morgan Kaufmann, 1998
- I. H. Witten and E. Frank, Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations, Morgan Kaufmann, 2nd ed. 2005

Architecture: Typical Data Mining System



Summary

- Data mining: Discovering interesting patterns from large amounts 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 information repositories
- Data mining functionalities: *characterization, discrimination, association, classification, clustering, outlier and trend analysis*, etc.
- Data mining systems and architectures
- Major issues in data mining

Recommended Text and Reference Books

- S. Chakrabarti. Mining the Web: Statistical Analysis of Hypertex and Semi-Structured Data. Morgan Kaufmann, 2002
- R. O. Duda, P. E. Hart, and D. G. Stork, Pattern Classification, 2ed., Wiley-Interscience, 2000
- T. Dasu and T. Johnson. Exploratory Data Mining and Data Cleaning. John Wiley & Sons, 2003
- U. M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, and R. Uthurusamy. Advances in Knowledge Discovery and Data Mining. AAAI/MIT Press, 1996
- U. Fayyad, G. Grinstein, and A. Wierse, Information Visualization in Data Mining and Knowledge Discovery, Morgan Kaufmann, 2001
- J. Han and M. Kamber. Data Mining: Concepts and Techniques. Morgan Kaufmann, 2nd ed., 2006
- D. J. Hand, H. Mannila, and P. Smyth, Principles of Data Mining, MIT Press, 2001
- T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer-Verlag, 2001
- B. Liu, Web Data Mining, Springer 2006.
- T. M. Mitchell, Machine Learning, McGraw Hill, 1997
- G. Piatetsky-Shapiro and W. J. Frawley. Knowledge Discovery in Databases. AAAI/MIT Press, 1991
- P.-N. Tan, M. Steinbach and V. Kumar, Introduction to Data Mining, Wiley, 2005
- S. M. Weiss and N. Indurkhya, Predictive Data Mining, Morgan Kaufmann, 1998
- I. H. Witten and E. Frank, Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations, Morgan Kaufmann, 2nd ed. 2005

Some more details

Why Data Mining?—Potential Applications

- Data analysis and decision support
  - Market analysis and management
    - Target marketing, customer relationship management (CRM), market basket analysis, cross selling, market segmentation
  - Risk analysis and management
    - Forecasting, customer retention, improved underwriting, quality control, competitive analysis
  - Fraud detection and detection of unusual patterns (*outliers*)
- Other Applications
  - Text mining (news group, email, documents) and Web mining
  - Stream data mining
  - Bioinformatics and bio-data analysis

Ex. 1: Market Analysis and Management

- Where does the data come from?—Credit card transactions, loyalty cards, discount coupons, customer complaint calls, plus (public) lifestyle studies
- Target marketing
  - Find clusters of “model” customers who share the same characteristics: interest, income level, spending habits, etc.
  - Determine customer purchasing patterns over time
- Cross-market analysis—Find associations/co-relations between product sales, & predict based on such association
- Customer profiling—What types of customers buy what products (clustering or classification)?
- Customer requirement analysis
  - Identify the best products for different groups of customers
  - Predict what factors will attract new customers
- Provision of summary information
  - Multidimensional summary reports
  - Statistical summary information (data central tendency and variation)

Ex. 2: Corporate Analysis & Risk Management

- Finance planning and asset evaluation
  - cash flow analysis and prediction
  - contingent claim analysis to evaluate assets
  - cross-sectional and time series analysis (financial-ratio, trend analysis, etc.)
- Resource planning
  - summarize and compare the resources and spending
- Competition
  - monitor competitors and market directions
  - group customers into classes and a class-based pricing procedure
  - set pricing strategy in a highly competitive market

Ex. 3: Fraud Detection & Mining Unusual Patterns

- Approaches: Clustering & model construction for frauds, outlier analysis
- Applications: Health care, retail, credit card service, telecomm.
  - Auto insurance: ring of collisions
  - Money laundering: suspicious monetary transactions
  - Medical insurance
    - Professional patients, ring of doctors, and ring of references
    - Unnecessary or correlated screening tests
  - Telecommunications: phone-call fraud
    - Phone call model: destination of the call, duration, time of day or week. Analyze patterns that deviate from an expected norm
  - Retail industry
    - Analysts estimate that 38% of retail shrink is due to dishonest employees
  - Anti-terrorism

Are All the "Discovered" Patterns Interesting?

- Data mining may generate thousands of patterns: Not all of them are interesting
  - Suggested approach: Human-centered, query-based, focused mining
- **Interestingness measures**
  - A pattern is interesting if it is easily understood by humans, valid on new or test data with some degree of certainty, potentially useful, novel, or validates some hypothesis that a user seeks to confirm
- **Objective vs. subjective interestingness measures**
  - Objective: based on statistics and structures of patterns, e.g., support, confidence, etc.
  - Subjective: based on user's belief in the data, e.g., unexpectedness, novelty, actionability, etc.

Find All and Only Interesting Patterns?

- Find all the interesting patterns: Completeness
  - Can a data mining system find all the interesting patterns? Do we need to find all of the interesting patterns?
  - Heuristic vs. exhaustive search
  - Association vs. classification vs. clustering
- Search for only interesting patterns: An optimization problem
  - Can a data mining system find only the interesting patterns?
  - Approaches
    - First generate all the patterns and then filter out the uninteresting ones
    - Generate only the interesting patterns—mining query optimization

Other Pattern Mining Issues

- Precise patterns vs. approximate patterns
  - Association and correlation mining: find sets of precise patterns
    - But approximate patterns can be more compact and sufficient
    - How to find high quality approximate patterns??
  - Gene sequence mining: approximate patterns are inherent
    - How to derive efficient approximate pattern mining algorithms??
- Constrained vs. non-constrained patterns
  - Why constraint-based mining?
  - What are the possible kinds of constraints? How to push constraints into the mining process?

Why Data Mining Query Language?

- Automated vs. query-driven?
  - Finding all the patterns autonomously in a database?—unrealistic because the patterns could be too many but uninteresting
- Data mining should be an interactive process
  - User directs what to be mined
- Users must be provided with a set of primitives to be used to communicate with the data mining system
- Incorporating these primitives in a data mining query language
  - More flexible user interaction
  - Foundation for design of graphical user interface
  - Standardization of data mining industry and practice

Primitives that Define a Data Mining Task

- Task-relevant data
  - Database or data warehouse name
  - Database tables or data warehouse cubes
  - Condition for data selection
  - Relevant attributes or dimensions
  - Data grouping criteria
- Type of knowledge to be mined
  - Characterization, discrimination, association, classification, prediction, clustering, outlier analysis, other data mining tasks
- Background knowledge
- Pattern interestingness measurements
- Visualization/presentation of discovered patterns

Primitive 3: Background Knowledge

- A typical kind of background knowledge: Concept hierarchies
- Schema hierarchy
  - E.g., street < city < province_or_state < country
- Set-grouping hierarchy
  - E.g., {20-39} = young, {40-59} = middle_aged
- Operation-derived hierarchy
  - email address: hagonzal@cs.uiuc.edu

    login-name < department < university < country
- Rule-based hierarchy
  - low_profit_margin (X) <= price(X, P_1) and cost (X, P_2) and (P_1 - P_2) < \$50

Primitive 4: Pattern Interestingness Measure

- Simplicity

  e.g., (association) rule length, (decision) tree size

- Certainty

  e.g., confidence, $P(A|B) = \#(A \text{ and } B)/ \#(B)$, classification reliability or accuracy, certainty factor, rule strength, rule quality, discriminating weight, etc.

- Utility

  potential usefulness, e.g., support (association), noise threshold (description)

- Novelty

  not previously known, surprising (used to remove redundant rules, e.g., Illinois vs. Champaign rule implication support ratio)

Primitive 5: Presentation of Discovered Patterns

- Different backgrounds/usages may require different forms of representation
  - E.g., rules, tables, crosstabs, pie/bar chart, etc.
- Concept hierarchy is also important
  - Discovered knowledge might be more understandable when represented at high level of abstraction
  - Interactive drill up/down, pivoting, slicing and dicing provide different perspectives to data
- Different kinds of knowledge require different representation: association, classification, clustering, etc.

DMQL—A Data Mining Query Language

- Motivation
  - A DMQL can provide the ability to support ad-hoc and interactive data mining
  - By providing a standardized language like SQL
    - Hope to achieve a similar effect like that SQL has on relational database
    - Foundation for system development and evolution
    - Facilitate information exchange, technology transfer, commercialization and wide acceptance
- Design
  - DMQL is designed with the primitives described earlier

An Example Query in DMQL

Example 1.11 Mining classification rules. Suppose, as a marketing manager of *AllElectronics*, you would like to classify customers based on their buying patterns. You are especially interested in those customers whose salary is no less than \$40,000, and who have bought more than \$1,000 worth of items, each of which is priced at no less than \$100. In particular, you are interested in the customer's age, income, the types of items purchased, the purchase location, and where the items were made. You would like to view the resulting classification in the form of rules. This data mining query is expressed in DMQL[3] as follows, where each line of the query has been enumerated to aid in our discussion.

```
use database AllElectronics_db
use hierarchy location_hierarchy for T.branch, age_hierarchy for C.age
mine classification as promising_customers
in relevance to C.age, C.income, I.type, I.place_made, T.branch
from customer C, item I, transaction T
where I.item_ID = T.item_ID and C.cust_ID = T.cust_ID
            and C.income ≥ 40,000 and I.price ≥ 100
group by T.cust_ID
having sum(I.price) ≥ 1,000
display as rules
```

Other Data Mining Languages & Standardization Efforts

- Association rule language specifications
  - MSQL (Imielinski & Virmani'99)
  - MineRule (Meo Psaila and Ceri'96)
  - Query flocks based on Datalog syntax (Tsur et al'98)
- OLEDB for DM (Microsoft'2000) and recently DMX (Microsoft SQLServer 2005)
  - Based on OLE, OLE DB, OLE DB for OLAP, C#
  - Integrating DBMS, data warehouse and data mining
- DMML (Data Mining Mark-up Language) by DMG (www.dmg.org)
  - Providing a platform and process structure for effective data mining
  - Emphasizing on deploying data mining technology to solve business problems

Integration of Data Mining and Data Warehousing

- **Data mining systems, DBMS, Data warehouse systems coupling**
  - No coupling, loose-coupling, semi-tight-coupling, tight-coupling
- **On-line analytical mining data**
  - integration of mining and OLAP technologies
- **Interactive mining multi-level knowledge**
  - Necessity of mining knowledge and patterns at different levels of abstraction by drilling/rolling, pivoting, slicing/dicing, etc.
- **Integration of multiple mining functions**
  - Characterized classification, first clustering and then association

Coupling Data Mining with DB/DW Systems

- No coupling—flat file processing, not recommended
- Loose coupling
  - Fetching data from DB/DW
- Semi-tight coupling—enhanced DM performance
  - Provide efficient implementation of a few data mining primitives in a DB/DW system, e.g., sorting, indexing, aggregation, histogram analysis, multiway join, precomputation of some stat functions
- Tight coupling—A uniform information processing environment
  - DM is smoothly integrated into a DB/DW system, mining query is optimized based on mining query, indexing, query processing methods, etc.