



DATA WAREHOUSING AND DATA MINING

Course code: AIT006

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Regulation: IARE R-16

BY

Dr. M Madhu Bala, Professor and HOD, Dept. of CSE

Dr. D Kishore Babu

Mr. Ch Suresh Kumar Raju

Mr. A Praveen, Ms. Ms. S Swarajya Laxmi, Ms. M GeethaYadav

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INSTITUTE OF AERONAUTICAL ENGINEERING

(Autonomous)

DUNDIGAL, HYDERABAD - 500 043

CO's

Course outcomes

- | | |
|-----|---|
| CO1 | Identifying necessity of Data Mining and Data Warehousing for the society. |
| CO2 | Familiar with the process of data analysis, identifying the problems, and choosing the relevant models and algorithms to apply. |
| CO3 | Develop skill in selecting the appropriate data mining algorithm for solving practical problems. |
| CO4 | Develop ability to design various algorithms based on data mining tools. |
| CO5 | Create further interest in research and design of new Data Mining techniques and concepts. |



MODULE- I

DATA WAREHOUSING

CLOs	Course Learning Outcome
CLO1	Learn data warehouse principles and find the differences between relational databases and data warehouse
CLO2	Explore on data warehouse architecture and its Components
CLO3	Learn Data warehouse schemas
CLO4	Differentiate different OLAP Architectures

What is a Data Warehouse?

- Defined in many different ways, but not rigorously.
 - A decision support database that is maintained **separately** from the organization’s operational database
 - Support **information processing** by providing a solid platform of consolidated, historical data for analysis.
- “A data warehouse is a subject-oriented, integrated, time-variant, and nonvolatile collection of data in support of management’s decision-making process.” —W. H. Inmon
- Data warehousing:
 - The process of constructing and using data warehouses

Data Warehouse—Subject-Oriented



- Organized around major subjects, such as **customer, product, sales**
- Focusing on the modeling and analysis of data for decision makers, not on daily operations or transaction processing
- Provide **a simple and concise** view around particular subject issues by **excluding data that are not useful in the decision support process**

Data Warehouse—Integrated



- Constructed by integrating multiple, heterogeneous data sources
 - relational databases, flat files, on-line transaction records
- Data cleaning and data integration techniques are applied.
 - Ensure consistency in naming conventions, encoding structures, attribute measures, etc. among different data sources
 - E.g., Hotel price: currency, tax, breakfast covered, etc.
 - When data is moved to the warehouse, it is converted.

Data Warehouse—Time Variant



- The time horizon for the data warehouse is significantly longer than that of operational systems
 - Operational database: current value data
 - Data warehouse data: provide information from a historical perspective (e.g., past 5-10 years)
- Every key structure in the data warehouse
 - Contains an element of time, explicitly or implicitly
 - But the key of operational data may or may not contain “time element”

Data Warehouse—Nonvolatile



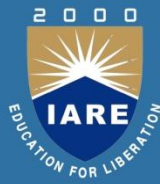
- A **physically separate store** of data transformed from the operational environment
- Operational **update of data does not occur** in the data warehouse environment
 - Does not require transaction processing, recovery, and concurrency control mechanisms
 - Requires only two operations in data accessing:
 - *initial loading of data* and *access of data*

Data Warehouse vs. Heterogeneous DBMS



- Traditional heterogeneous DB integration: A **query driven** approach
 - Build **wrappers/mediators** on top of heterogeneous databases
 - When a query is posed to a client site, a meta-dictionary is used to translate the query into queries appropriate for individual heterogeneous sites involved, and the results are integrated into a global answer set
 - Complex information filtering, compete for resources
- Data warehouse: **update-driven**, high performance
 - Information from heterogeneous sources is integrated in advance and stored in warehouses for direct query and analysis

Data Warehouse vs. Operational DBMS



- OLTP (on-line transaction processing)
 - Major task of traditional relational DBMS
 - Day-to-day operations: purchasing, inventory, banking, manufacturing, payroll, registration, accounting, etc.
- OLAP (on-line analytical processing)
 - Major task of data warehouse system
 - Data analysis and decision making
- Distinct features (OLTP vs. OLAP):
 - User and system orientation: customer vs. market
 - Data contents: current, detailed vs. historical, consolidated
 - Database design: ER + application vs. star + subject
 - View: current, local vs. evolutionary, integrated
 - Access patterns: update vs. read-only but complex queries

OLTP vs. OLAP

	OLTP	OLAP
users	clerk, IT professional	knowledge worker
function	day to day operations	decision support
DB design	application-oriented	subject-oriented
data	current, up-to-date detailed, flat relational isolated	historical, summarized, multidimensional integrated, consolidated
usage	repetitive	ad-hoc
access	read/write index/hash on prim. key	lots of scans
unit of work	short, simple transaction	complex query
# records accessed	tens	millions
#users	thousands	hundreds
DB size	100MB-GB	100GB-TB
metric	transaction throughput	query throughput, response

Why a Separate Data Warehouse?



- High performance for both systems
 - DBMS— tuned for OLTP: access methods, indexing, concurrency control, recovery
 - Warehouse—tuned for OLAP: complex OLAP queries, multidimensional view, consolidation
- Different functions and different data:
 - [missing data](#): Decision support requires historical data which operational DBs do not typically maintain
 - [data consolidation](#): DS requires consolidation (aggregation, summarization) of data from heterogeneous sources
 - [data quality](#): different sources typically use inconsistent data representations, codes and formats which have to be reconciled
- Note: There are more and more systems which perform OLAP analysis directly on relational databases

From Tables and Spreadsheets to Data Cubes



- A data warehouse is based on a **multidimensional data model** which views data in the form of a data cube
- A data cube, such as **sales**, allows data to be modeled and viewed in multiple dimensions
 - Dimension tables, such as **item (item_name, brand, type)**, or **time(day, week, month, quarter, year)**
 - Fact table contains measures (such as **dollars_sold**) and keys to each of the related dimension tables
- In data warehousing literature, an n-D base cube is called a **base cuboid**. The top most 0-D cuboid, which holds the highest-level of summarization, is called the **apex cuboid**. The lattice of cuboids forms a **data cube**.

Multidimensional Data Model

<i>location = "Vancouver"</i>				
<i>item (type)</i>				
<i>time (quarter)</i>	<i>home</i>			
	<i>entertainment</i>	<i>computer</i>	<i>phone</i>	<i>security</i>
Q1	605	825	14	400
Q2	680	952	31	512
Q3	812	1023	30	501
Q4	927	1038	38	580

Fig: A 2-D view of sales data for *AllElectronics* according to the dimensions *time* and *item*, where the sales are from branches located in the city of Vancouver.

Multidimensional Data Model

<i>location</i> = "Chicago"					<i>location</i> = "New York"				<i>location</i> = "Toronto"				<i>location</i> = "Vancouver"			
<i>Item</i>					<i>Item</i>				<i>Item</i>				<i>Item</i>			
<i>home</i>					<i>home</i>				<i>home</i>				<i>home</i>			
<i>time</i>	<i>ent.</i>	<i>comp.</i>	<i>phone</i>	<i>sec.</i>	<i>ent.</i>	<i>comp.</i>	<i>phone</i>	<i>sec.</i>	<i>ent.</i>	<i>comp.</i>	<i>phone</i>	<i>sec.</i>	<i>ent.</i>	<i>comp.</i>	<i>phone</i>	<i>sec.</i>
Q1	854	882	89	623	1087	968	38	872	818	746	43	591	605	825	14	400
Q2	943	890	64	698	1130	1024	41	925	894	769	52	682	680	952	31	512
Q3	1032	924	59	789	1034	1048	45	1002	940	795	58	728	812	1023	30	501
Q4	1129	992	63	870	1142	1091	54	984	978	864	59	784	927	1038	38	580

Fig: A 3-D view of sales data for *AllElectronics*, according to the dimensions *time*, *item*, and *location*.

Multidimensional Data Model

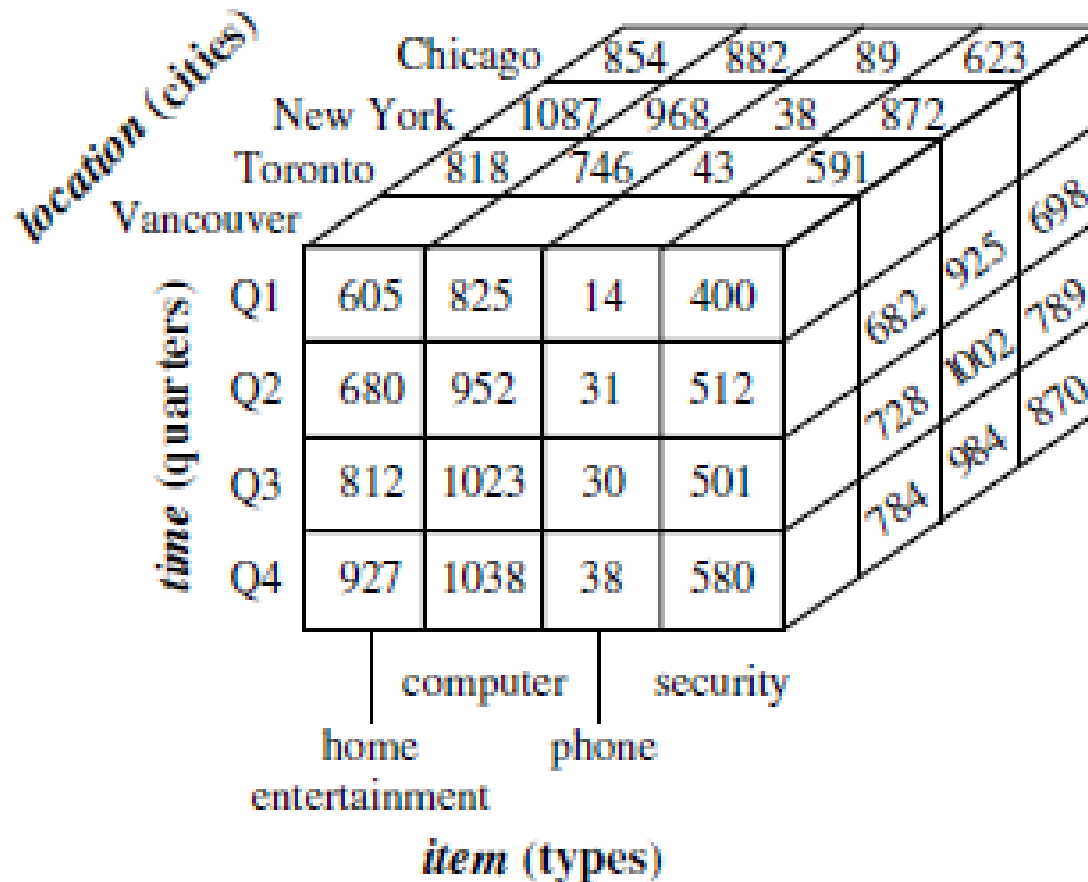


Fig: 3-D data cube representation of the data

Multidimensional Data Model

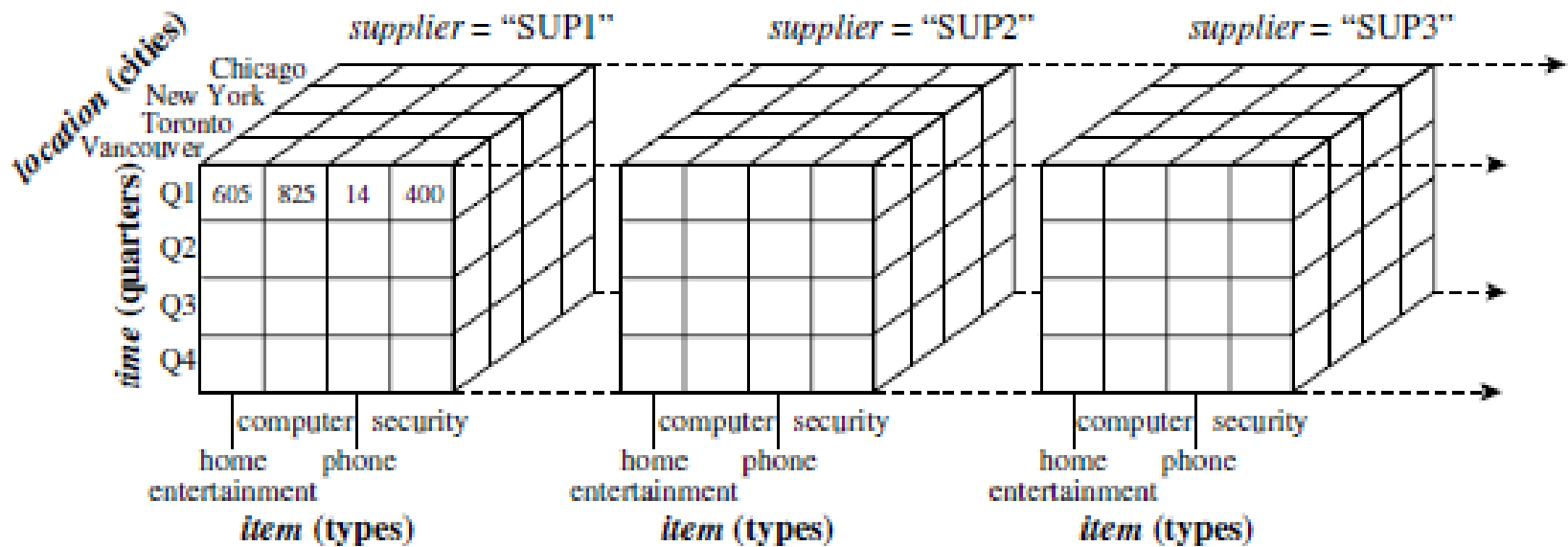


Fig: A 4-D data cube representation of sales data, according to the dimensions *time*, *item*, *location*, and *supplier*.

Multidimensional Data Model

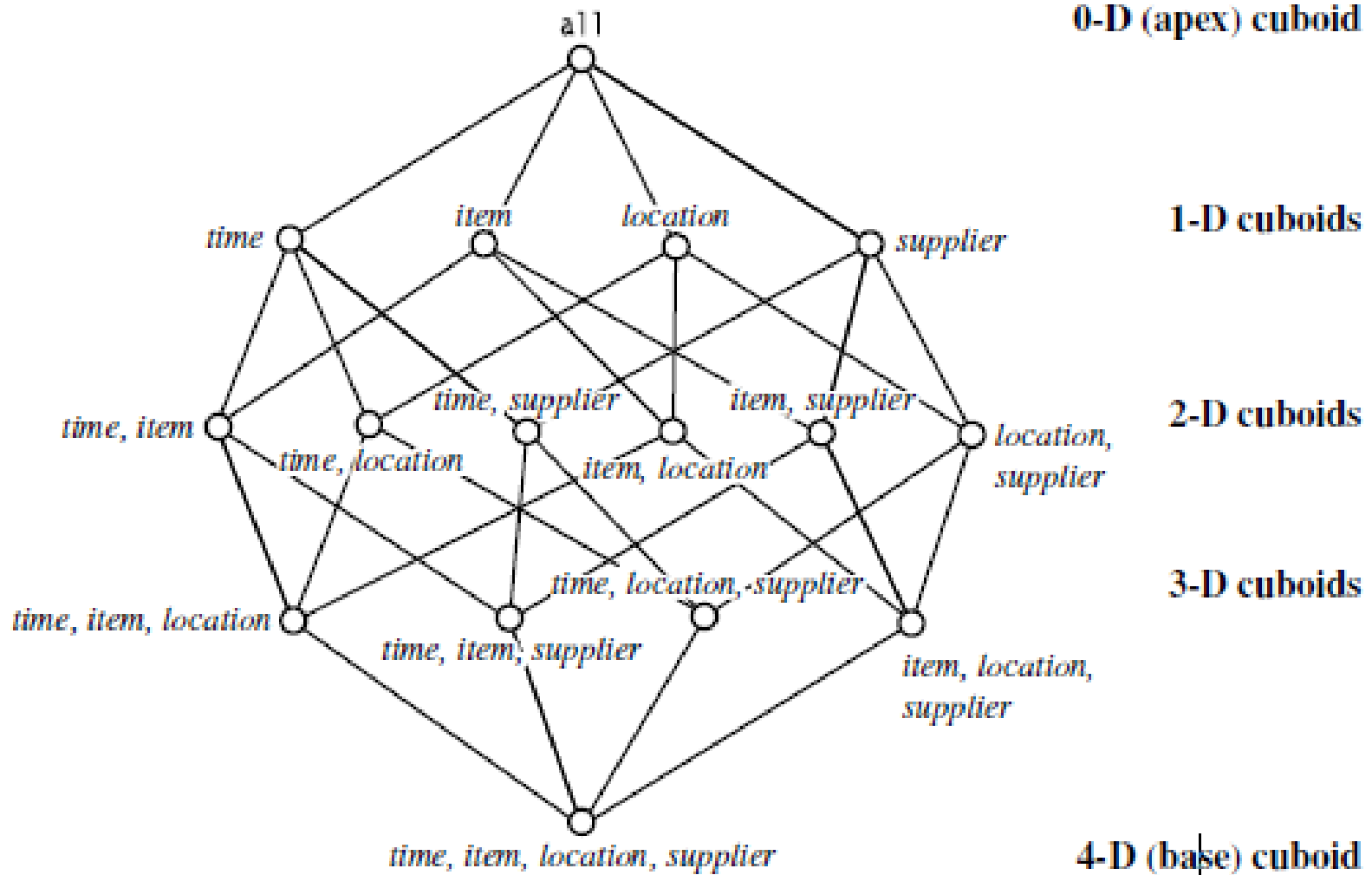
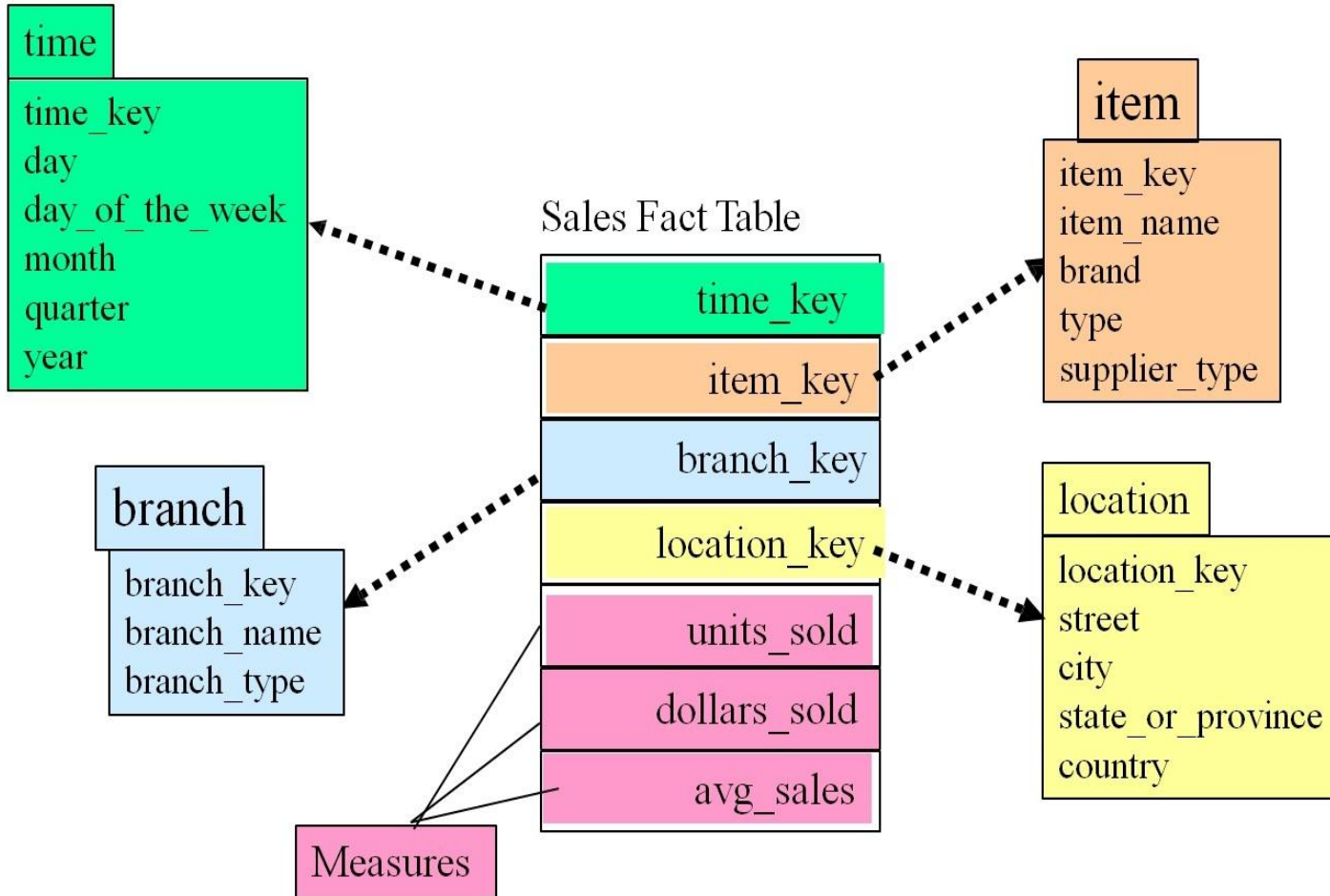


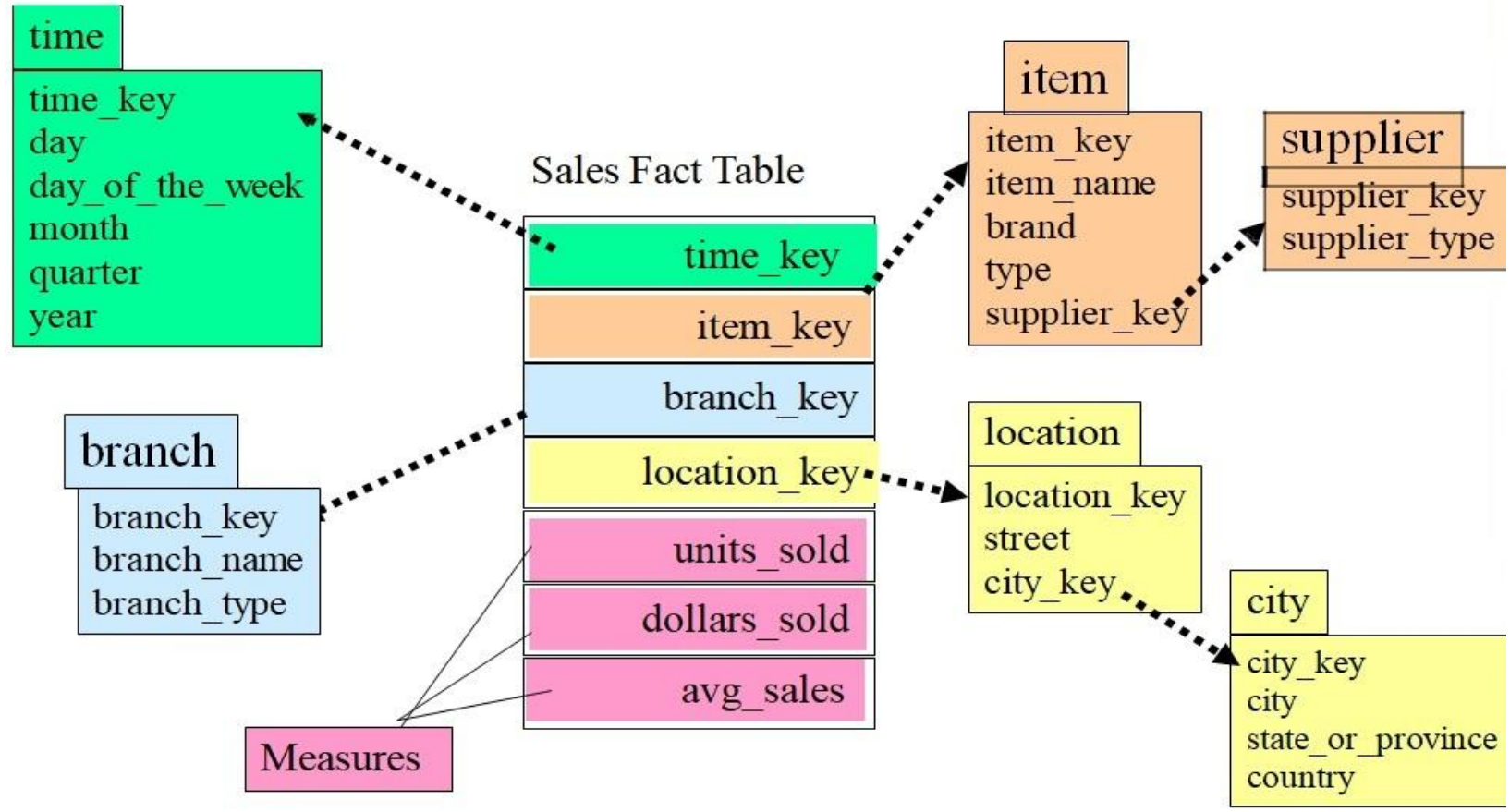
Fig: Lattice of cuboids

- Modeling data warehouses: dimensions & measures
 - Star schema: A fact table in the middle connected to a set of dimension tables
 - Snowflake schema: A refinement of star schema where some dimensional hierarchy is **normalized** into a set of smaller dimension tables, forming a shape similar to snowflake
 - Fact constellations: Multiple fact tables share dimension tables, viewed as a collection of stars, therefore called **galaxy schema** or fact constellation

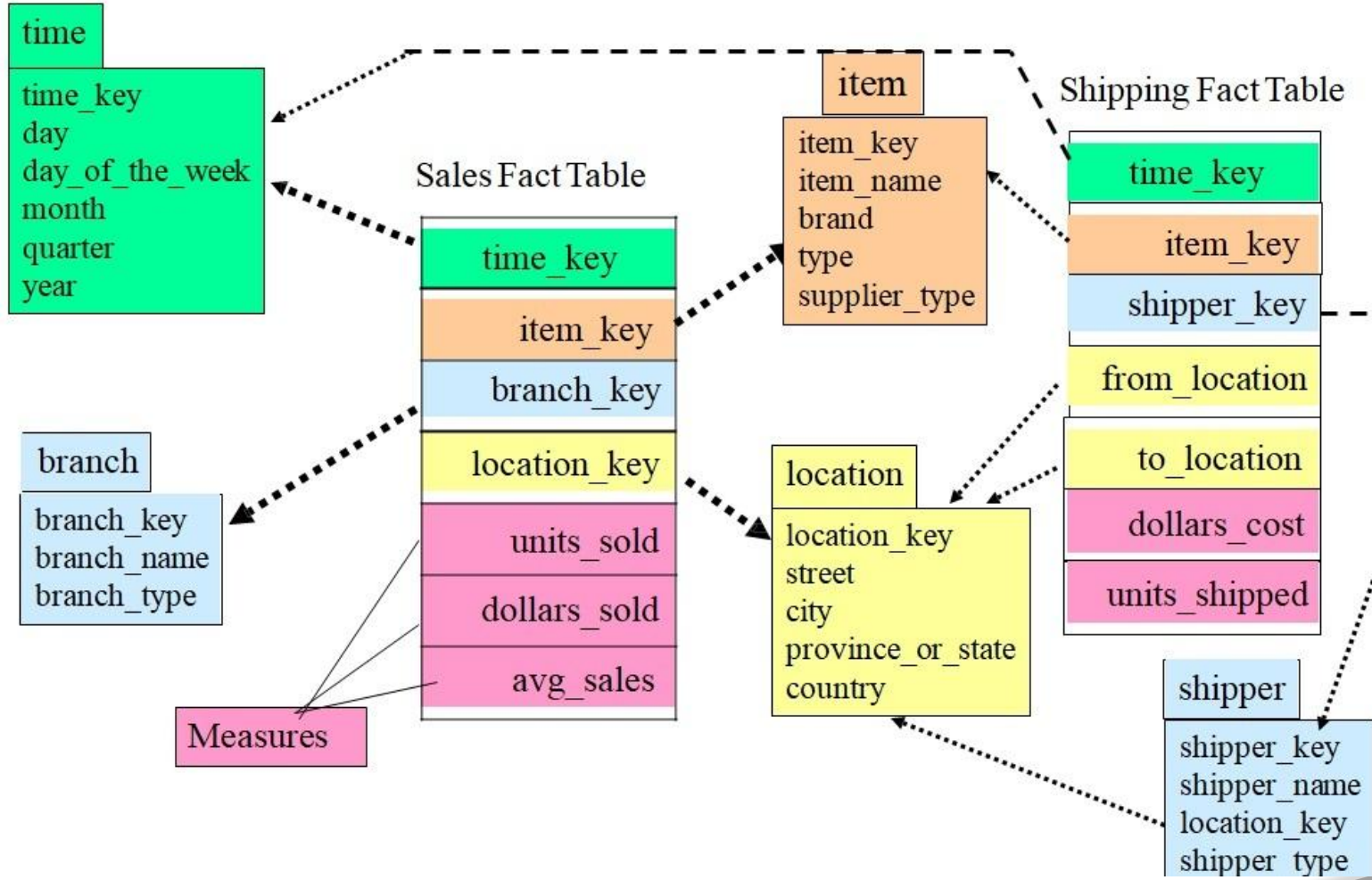
Example of Star Schema



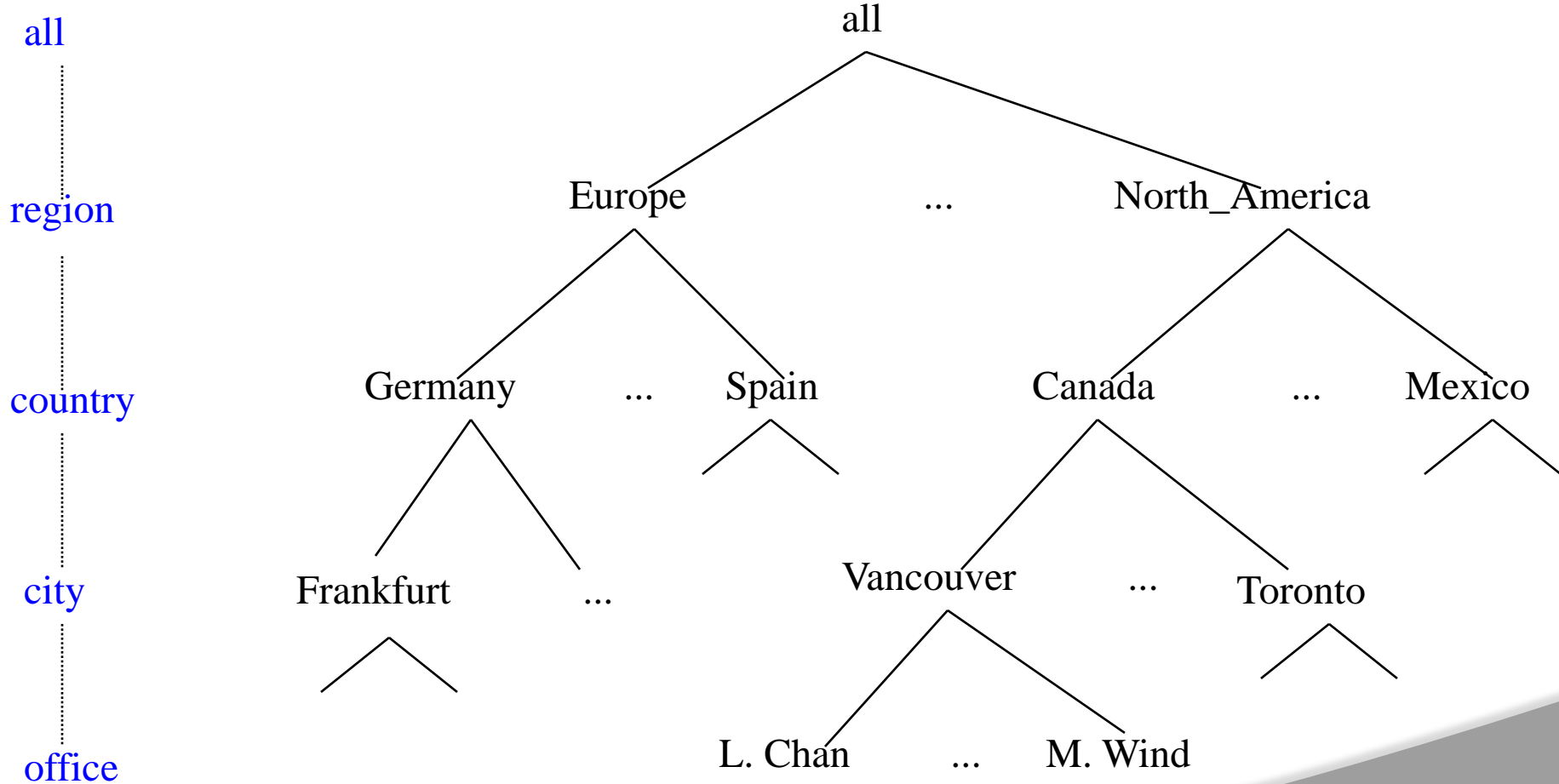
Example of Snowflake Schema



Example of Fact Constellation



A Concept Hierarchy: Dimension (location)



Data Cube Measures: Three Categories

- Distributive: if the result derived by applying the function to n aggregate values is the same as that derived by applying the function on all the data without partitioning
 - E.g., `count()`, `sum()`, `min()`, `max()`
- Algebraic: if it can be computed by an algebraic function with M arguments (where M is a bounded integer), each of which is obtained by applying a distributive aggregate function
 - E.g., `avg()`, `min_N()`, `standard_deviation()`
- Holistic: if there is no constant bound on the storage size needed to describe a subaggregate.
 - E.g., `median()`, `mode()`, `rank()`

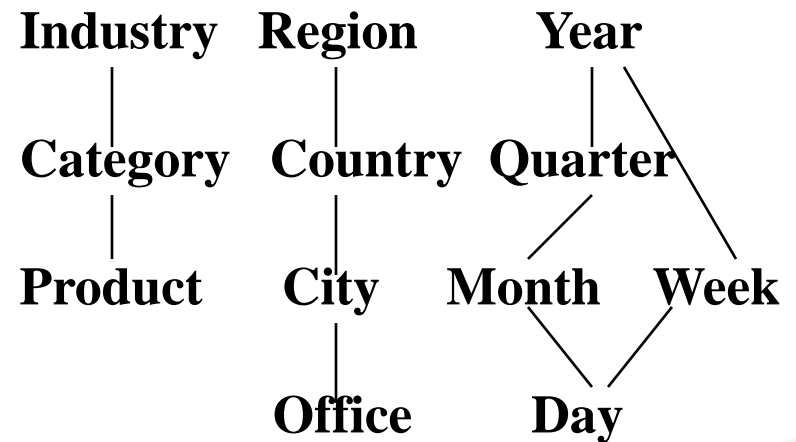
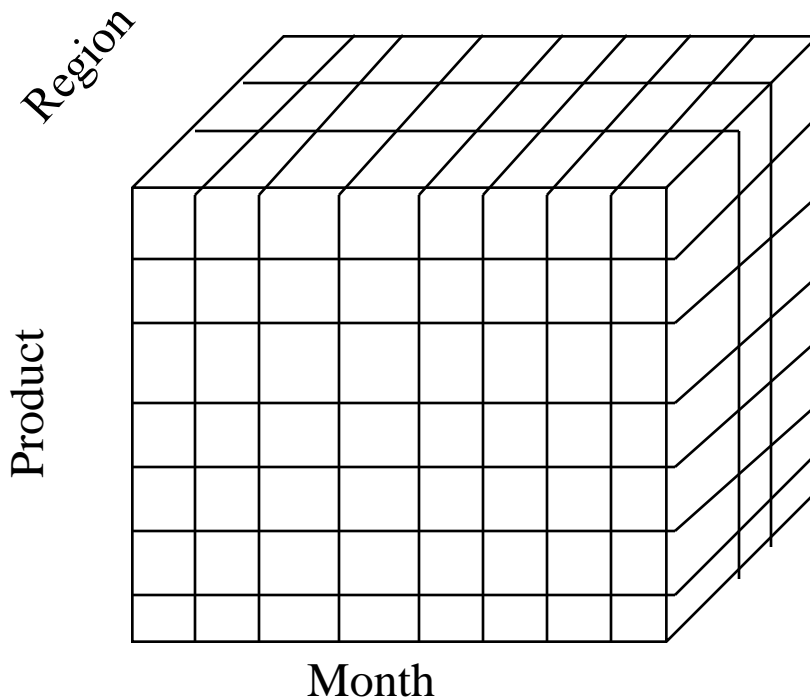
Three Data Warehouse Models

- **Enterprise warehouse**
 - collects all of the information about subjects spanning the entire organization
- **Data Mart**
 - a subset of corporate-wide data that is of value to a specific groups of users. Its scope is confined to specific, selected groups, such as marketing data mart
 - Independent vs. dependent (directly from warehouse) data mart
- **Virtual warehouse**
 - A set of views over operational databases
 - Only some of the possible summary views may be materialized

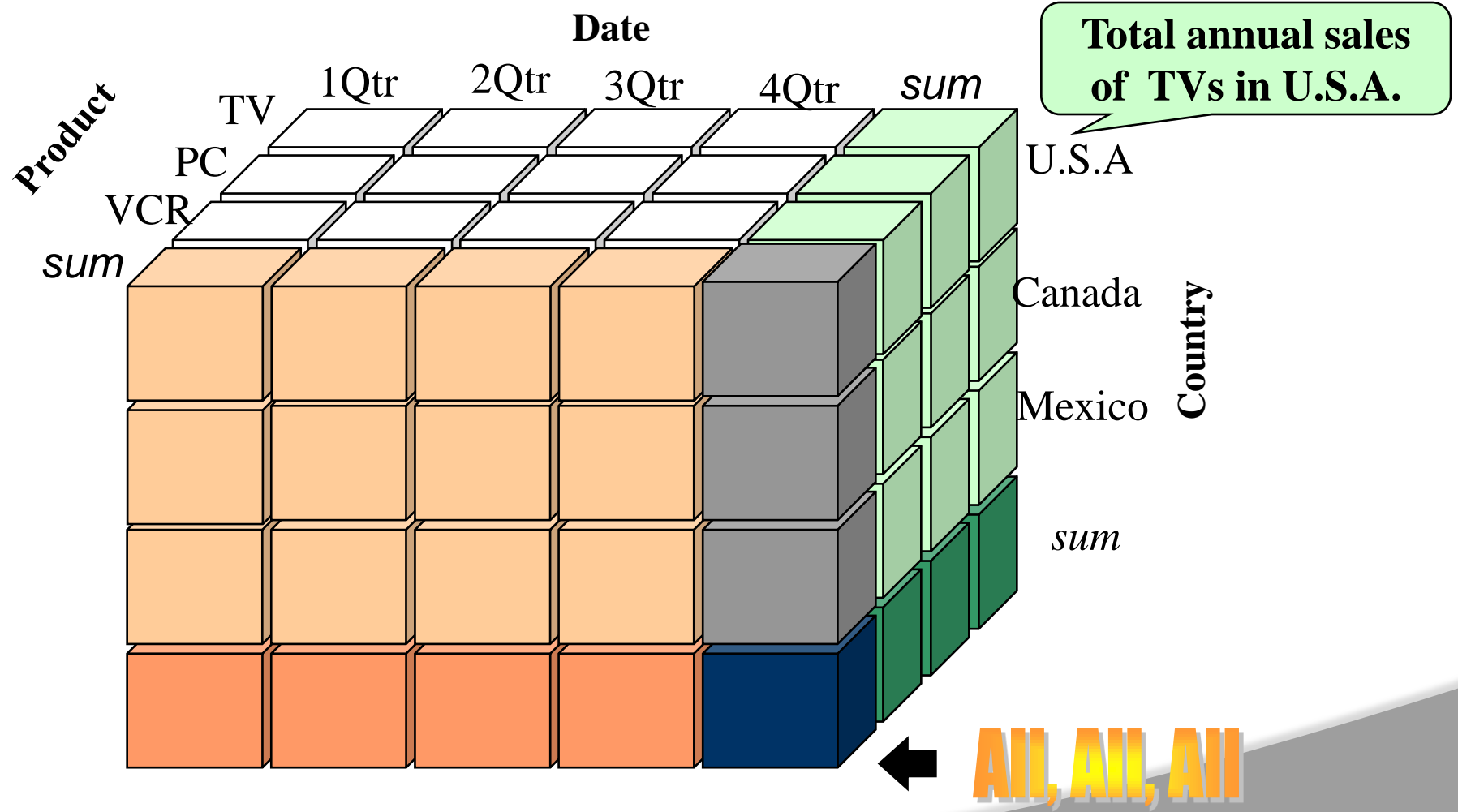
Multidimensional Data

- Sales volume as a function of product, month, and region

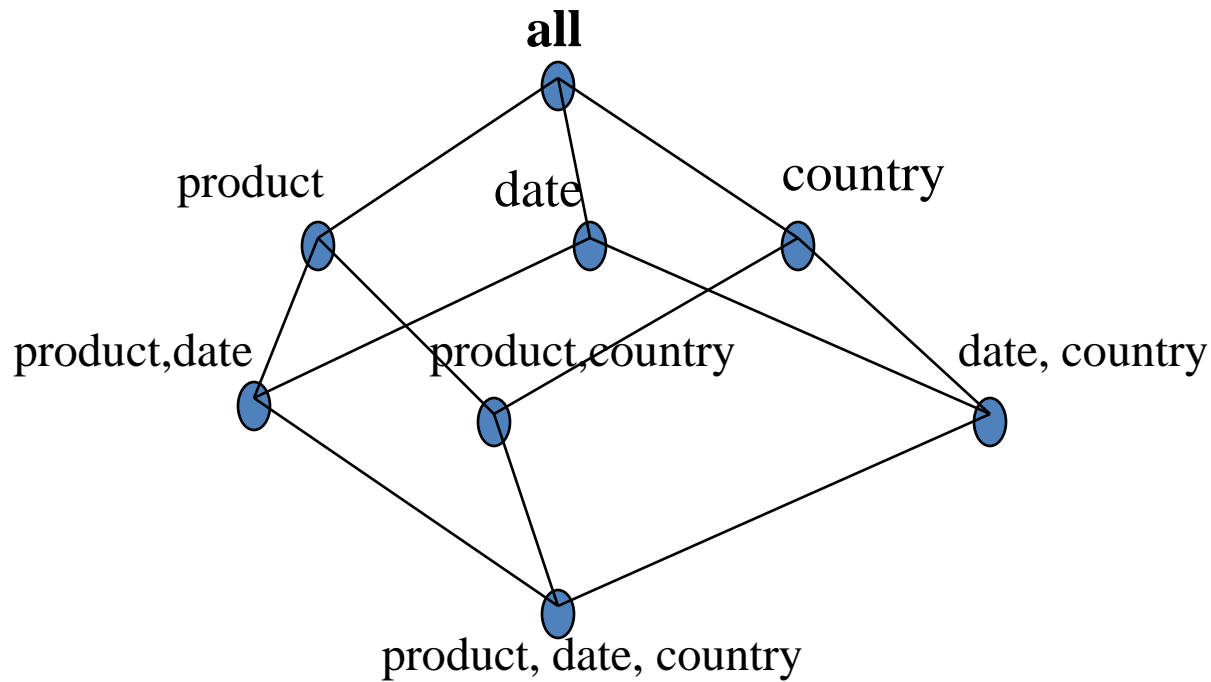
Dimensions: *Product, Location, Time*
Hierarchical summarization paths



A Sample Data Cube



Cuboids Corresponding to the Cube



0-D (*apex*) cuboid

1-D cuboids

2-D cuboids

3-D (*base*) cuboid

Typical OLAP Operations

- Roll up (drill-up): summarize data
 - *by climbing up hierarchy or by dimension reduction*
- Drill down (roll down): reverse of roll-up
 - *from higher level summary to lower level summary or detailed data, or introducing new dimensions*
- Slice and dice: *project and select*
- Pivot (rotate):
 - *reorient the cube, visualization, 3D to series of 2D planes*
- Other operations
 - *drill across: involving (across) more than one fact table*
 - *drill through: through the bottom level of the cube to its back-end relational tables (using SQL)*

Design of Data Warehouse

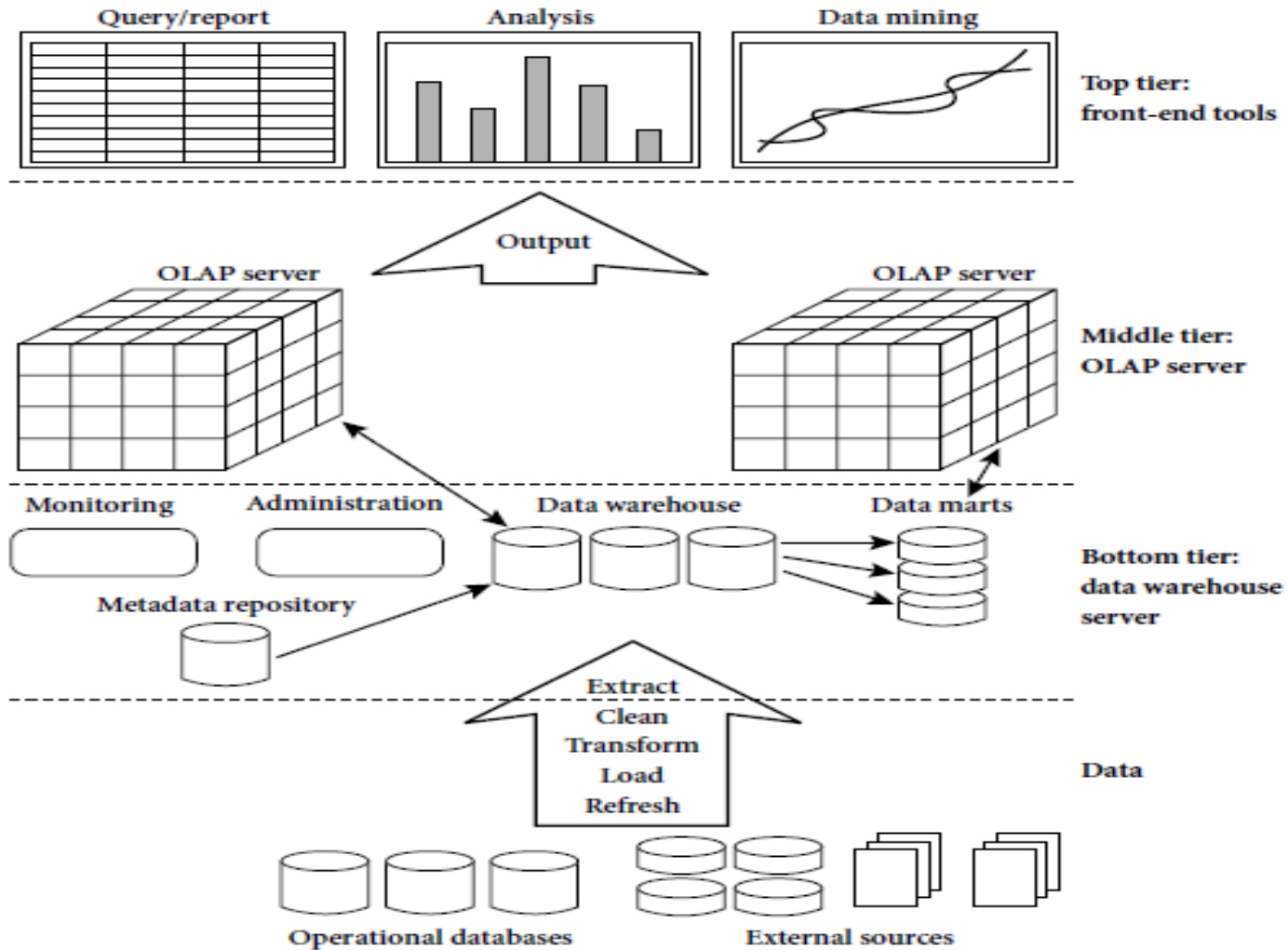
A Business Analysis Framework

- Four views regarding the design of a data warehouse
 - Top-down view
 - allows selection of the relevant information necessary for the data warehouse
 - Data source view
 - exposes the information being captured, stored, and managed by operational systems
 - Data warehouse view
 - consists of fact tables and dimension tables
 - Business query view
 - sees the perspectives of data in the warehouse from the view of end-user

Data Warehouse Design Process

- Top-down, bottom-up approaches or a combination of both
 - Top-down: Starts with overall design and planning (mature)
 - Bottom-up: Starts with experiments and prototypes (rapid)
- From software engineering point of view
 - Waterfall: structured and systematic analysis at each step before proceeding to the next
 - Spiral: rapid generation of increasingly functional systems, short turn around time, quick turn around
- Typical data warehouse design process
 - Choose a **business process** to model, e.g., orders, invoices, etc.
 - Choose the **grain (atomic level of data)** of the business process
 - Choose the **dimensions** that will apply to each fact table record
 - Choose the **measure** that will populate each fact table record

A three-tier data warehousing architecture

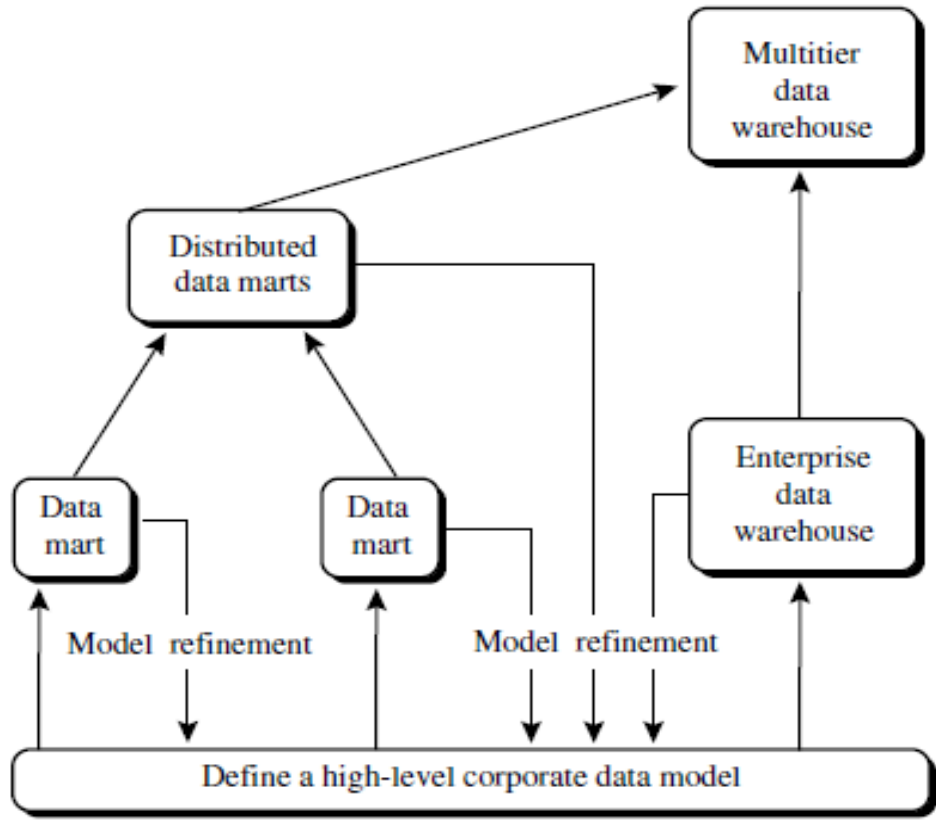


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Data Warehouse Development

A Recommended Approach



- Data extraction
 - get data from multiple, heterogeneous, and external sources
- Data cleaning
 - detect errors in the data and rectify them when possible
- Data transformation
 - convert data from legacy or host format to warehouse format
- Load
 - sort, summarize, consolidate, compute views, check integrity, and build indices and partitions
- Refresh
 - propagate the updates from the data sources to the warehouse

Metadata Repository

- Meta data is the data defining warehouse objects. It stores:
- Description of the structure of the data warehouse
 - schema, view, dimensions, hierarchies, derived data defn, data mart locations and contents
- Operational meta-data
 - data lineage (history of migrated data and transformation path), currency of data (active, archived, or purged), monitoring information (warehouse usage statistics, error reports, audit trails)
- The algorithms used for summarization
- The mapping from operational environment to the data warehouse
- Data related to system performance
 - warehouse schema, view and derived data definitions
- Business data
 - business terms and definitions, ownership of data, charging policies

OLAP Server Architectures

- [Relational OLAP \(ROLAP\)](#)
 - Use relational or extended-relational DBMS to store and manage warehouse data and OLAP middle ware
 - Include optimization of DBMS backend, implementation of aggregation navigation logic, and additional tools and services
 - Greater scalability
- [Multidimensional OLAP \(MOLAP\)](#)
 - Sparse array-based multidimensional storage engine
 - Fast indexing to pre-computed summarized data
- [Hybrid OLAP \(HOLAP\)](#) (e.g., Microsoft SQLServer)
 - Flexibility, e.g., low level: relational, high-level: array
- [Specialized SQL servers](#) (e.g., Redbricks)
 - Specialized support for SQL queries over star/snowflake schemas

Extraction, Transformation, and Loading (ETL)



- **Data extraction**
 - get data from multiple, heterogeneous, and external sources
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 - sort, summarize, consolidate, compute views, check integrity, and build indices and partitions
- **Refresh**
 - propagate the updates from the data sources to the warehouse

Data Warehouse Implementation

Efficient Data Cube Computation

- Data cube can be viewed as a lattice of cuboids
 - The bottom-most cuboid is the base cuboid
 - The top-most cuboid (apex) contains only one cell
 - **How many cuboids** in an n-dimensional cube with L levels?

- Materialization of data cube $T = \prod_{i=1}^n (L_i + 1)$
 - Materialize every (cuboid) (**full materialization**), none (**no materialization**), or some (**partial materialization**)
 - Selection of which cuboids to materialize
 - Based on size, sharing, access frequency, etc.

Indexing OLAP Data: Bitmap Index

- Index on a particular column
- Each value in the column has a bit vector: bit-op is fast
- The length of the bit vector: # of records in the base table
- The i -th bit is set if the i -th row of the base table has the value for the indexed column
- not suitable for high cardinality domains
- A recent bit compression technique, Word-Aligned Hybrid (WAH), makes it work for high cardinality domain as well [Wu, et al. TODS'06]

Base table

Cust	Region	Type
C1	Asia	Retail
C2	Europe	Dealer
C3	Asia	Dealer
C4	America	Retail
C5	Europe	Dealer

Index on Region

RecID	Asia	Europe	America
1	1	0	0
2	0	1	0
3	1	0	0
4	0	0	1
5	0	1	0

Index on Type

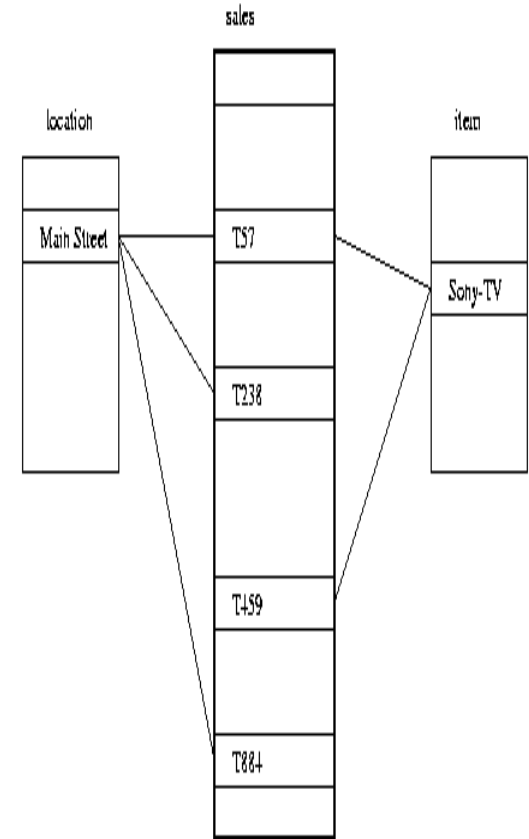
RecID	Retail	Dealer
1	1	0
2	0	1
3	0	1
4	1	0
5	0	1

From On-Line Analytical Processing (OLAP) to On Line Analytical Mining (OLAM)

- Why **online analytical mining**?
 - High quality of data in data warehouses
 - DW contains integrated, consistent, cleaned data
 - Available information processing structure surrounding data warehouses
 - ODBC, OLEDB, Web accessing, service facilities, reporting and OLAP tools
 - OLAP-based exploratory data analysis
 - Mining with drilling, dicing, pivoting, etc.
 - On-line selection of data mining functions
 - Integration and swapping of multiple mining functions, algorithms, and tasks

Indexing OLAP Data: Join Indices

- Join index: $Jl(R\text{-id}, S\text{-id})$ where $R (R\text{-id}, \dots) \triangleright \triangleleft S (S\text{-id}, \dots)$
- Traditional indices map the values to a list of record ids
 - It materializes relational join in JI file and speeds up relational join
- In data warehouses, join index relates the values of the dimensions of a star schema to rows in the fact table.
 - E.g. fact table: *Sales* and two dimensions *city* and *product*
 - A join index on *city* maintains for each distinct city a list of R-IDs of the tuples recording the Sales in the city
 - Join indices can span multiple dimensions



The “Compute Cube” Operator

- Cube definition and computation in DMQL

```
define cube sales [item, city, year]: sum (sales_in_dollars)
```

```
compute cube sales
```

- Transform it into a SQL-like language (with a new operator **cube by**, introduced by Gray et al.'96)

```
SELECT item, city, year, SUM (amount)
```

```
FROM SALES
```

```
CUBE BY item, city, year
```

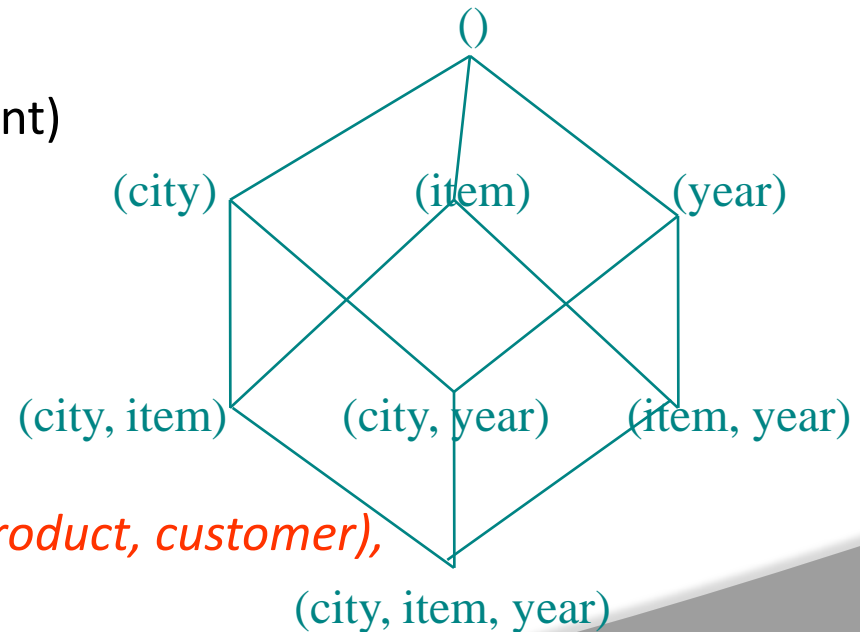
- Need compute the following Group-Bys

```
(date, product, customer),
```

```
(date,product),(date, customer), (product, customer),
```

```
(date), (product), (customer)
```

```
()
```



Data Warehouse Usage



- Three kinds of data warehouse applications
 - Information processing
 - supports querying, basic statistical analysis, and reporting using crosstabs, tables, charts and graphs
 - Analytical processing
 - multidimensional analysis of data warehouse data
 - supports basic OLAP operations, slice-dice, drilling, pivoting
 - Data mining
 - knowledge discovery from hidden patterns
 - supports associations, constructing analytical models, performing classification and prediction, and presenting the mining results using visualization tools

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MODULE- II

DATA MINING

CLOs	Course Learning Outcome
CLO5	Understand Data Mining concepts and knowledge discovery process
CLO6	Explore on Data preprocessing techniques
CLO7	Apply task related attribute selection and transformation techniques
CLO8	Understand the Association rule mining Problem

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

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?

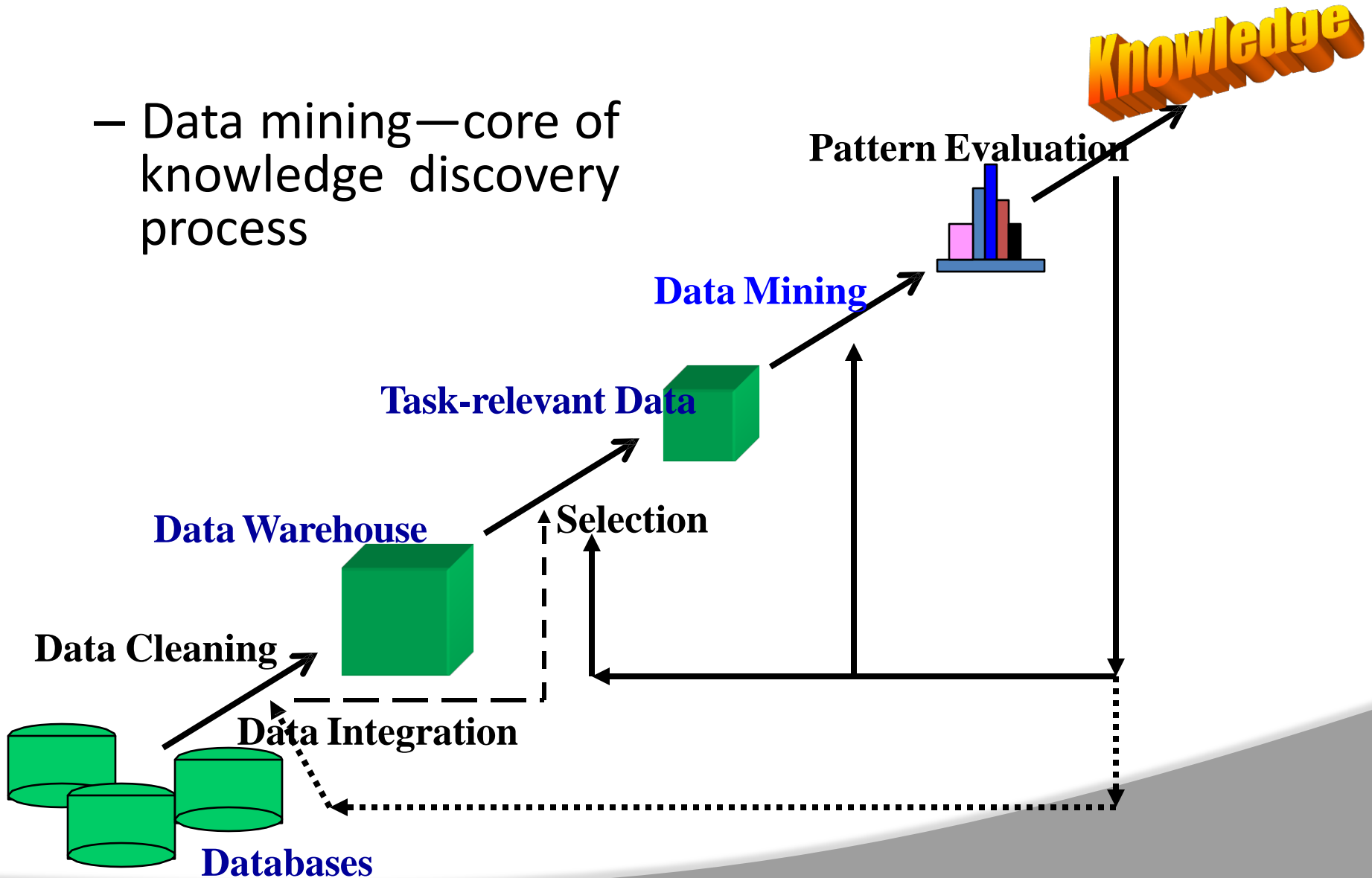


- Data mining (knowledge discovery from data)
 - Extraction of interesting (non-trivial, implicit, previously unknown and potentially useful) patterns or knowledge from huge amount of data
 - Data mining: a misnomer?
- Alternative names
 - Knowledge discovery (mining) in databases (KDD), knowledge extraction,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

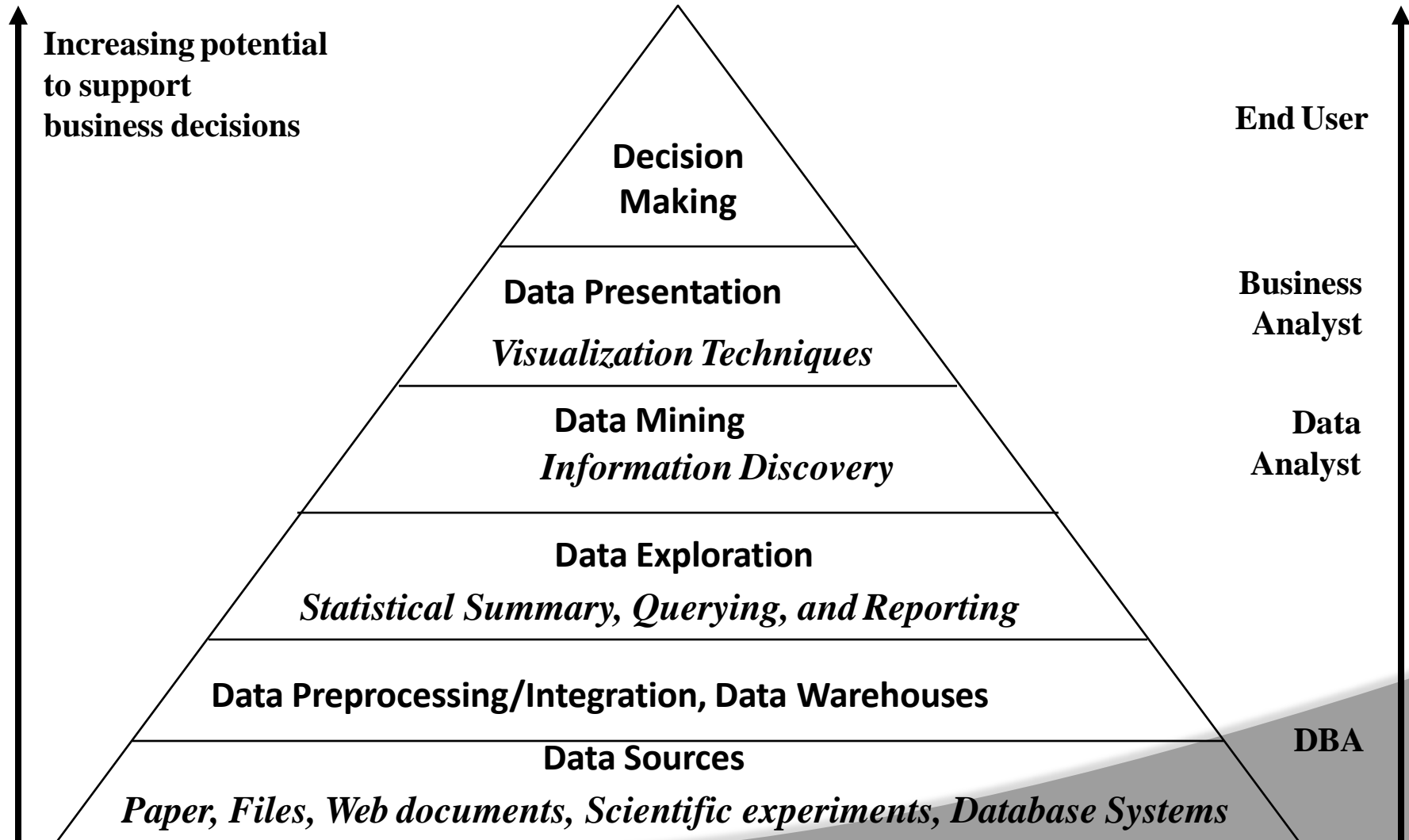


Knowledge Discovery (KDD) Process

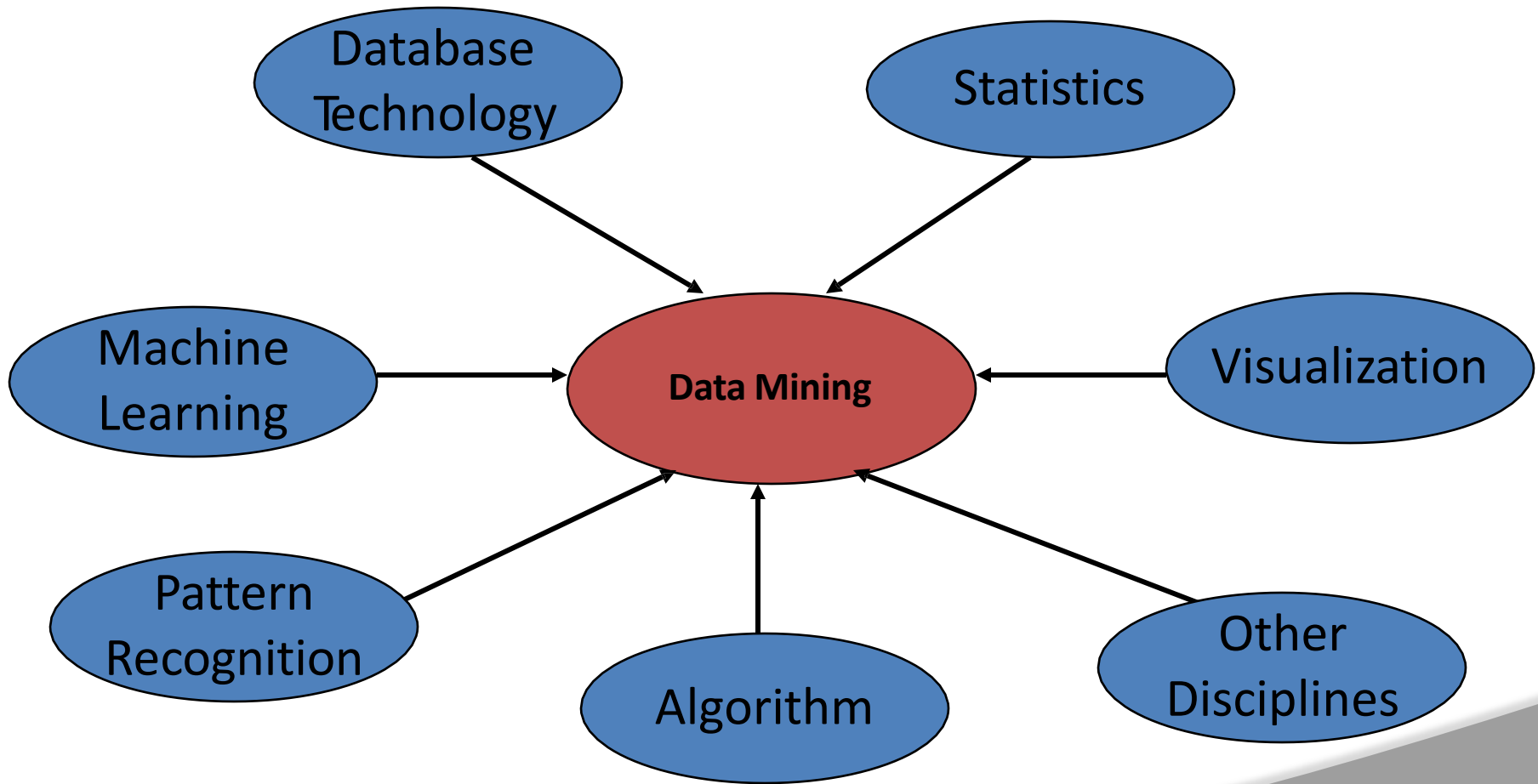
- Data mining—core of knowledge discovery process



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
 - 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

Multi-Dimensional View of Data Mining

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

Data Mining: Classification Schemes



- General functionality
 - Descriptive data mining
 - Predictive data mining
- Different views lead to different classifications
 - **Data** view: Kinds of data to be mined
 - **Knowledge** view: Kinds of knowledge to be discovered
 - **Method** view: Kinds of techniques utilized
 - **Application** view: Kinds of applications adapted

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 Functionalities

- Multidimensional concept description: Characterization and discrimination
 - Generalize, summarize, and contrast data characteristics, e.g., dry vs. wet regions
- Frequent patterns, association, correlation vs. causality
 - Diaper → Beer [0.5%, 75%] (Correlation or causality?)
- Classification and prediction
 - Construct models (functions) that 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 or missing numerical values

Data Mining Functionalities (2)

- Cluster analysis
 - Class label is unknown: Group data to form new classes, e.g., cluster houses to find distribution patterns
 - Maximizing intra-class similarity & minimizing interclass similarity
- Outlier analysis
 - Outlier: Data object that does not comply with the general behavior of the data
 - Noise or exception? Useful in fraud detection, rare events analysis
- Trend and evolution analysis
 - Trend and deviation: e.g., regression analysis
 - Sequential pattern mining: e.g., digital camera → large SD memory
 - Periodicity analysis
 - Similarity-based analysis
- Other pattern-directed or statistical analyses

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

- 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

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

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?

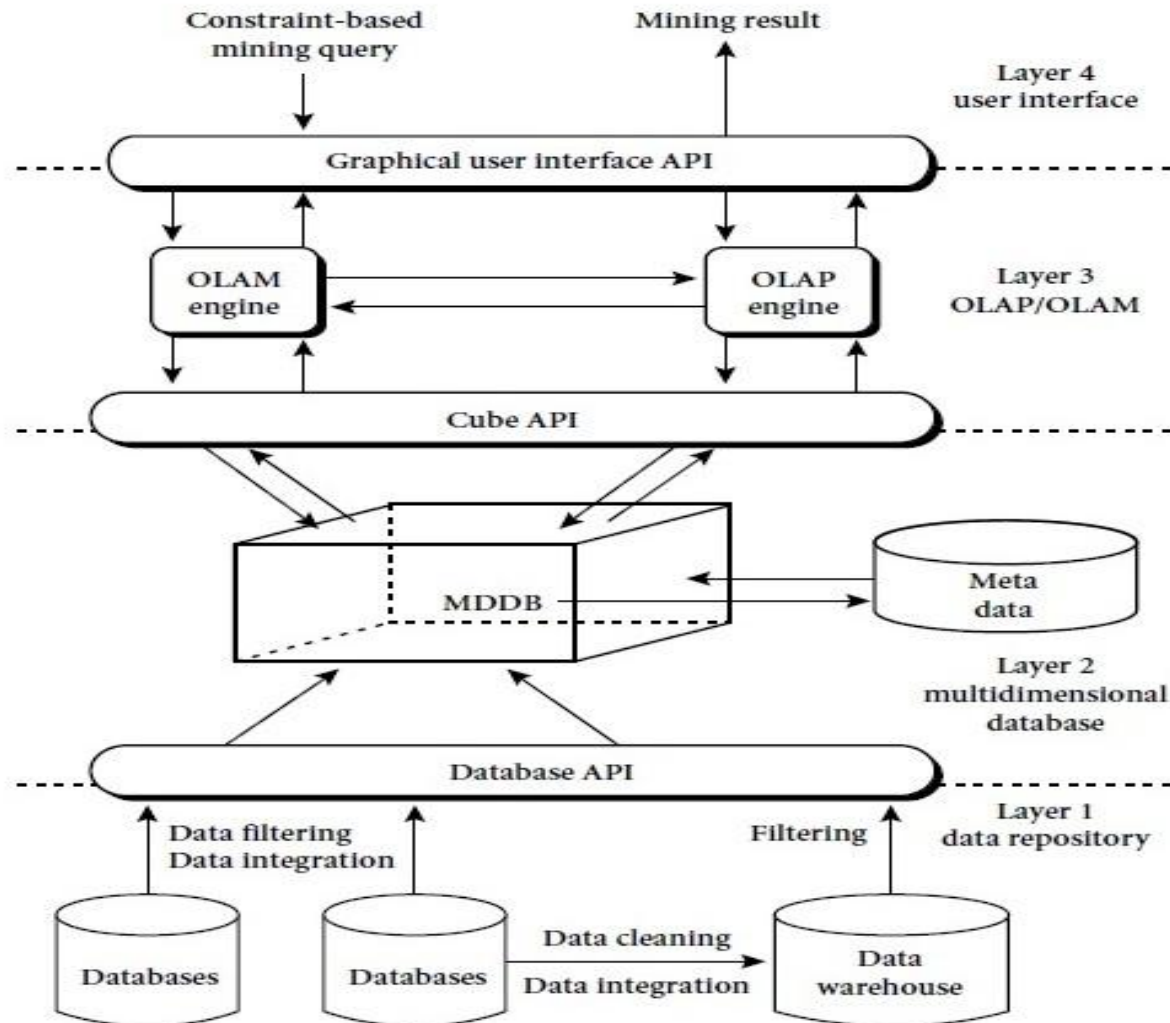


- Find all the interesting patterns: Completeness
 - Can a data mining system find all the interesting patterns? Do we need to find all of the interesting patterns?
 - Heuristic vs. exhaustive search
 - Association vs. classification vs. clustering
- Search for only interesting patterns: An optimization problem
 - Can a data mining system find only the interesting patterns?
 - Approaches
 - First general 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: possible 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?

Architecture: Typical Data Mining



Why Data Preprocessing?

- Data in the real world is dirty
 - **incomplete**: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
 - e.g., occupation=""
 - **noisy**: containing errors or outliers
 - e.g., Salary="-10"
 - **inconsistent**: containing discrepancies in codes or names
 - e.g., Age="42" Birthday="03/07/1997"
 - e.g., Was rating "1,2,3", now rating "A, B, C"
 - e.g., discrepancy between duplicate records

Why Is Data Dirty?

- Incomplete data may come from
 - “Not applicable” data value when collected
 - Different considerations between the time when the data was collected and when it is analyzed.
 - Human/hardware/software problems
- Noisy data (incorrect values) may come from
 - Faulty data collection instruments
 - Human or computer error at data entry
 - Errors in data transmission
- Inconsistent data may come from
 - Different data sources
 - Functional dependency violation (e.g., modify some linked data)
- Duplicate records also need data cleaning

Why Is Data Preprocessing

- No quality data, no quality mining results!
 - Quality decisions must be based on quality data
 - e.g., duplicate or missing data may cause incorrect or even misleading statistics.
 - Data warehouse needs consistent integration of quality data
- Data extraction, cleaning, and transformation comprises the majority of the work of building a data warehouse

- A well-accepted multidimensional view:
 - Accuracy
 - Completeness
 - Consistency
 - Timeliness
 - Believability
 - Value added
 - Interpretability
 - Accessibility
- Broad categories:
 - Intrinsic, contextual, representational, and accessibility

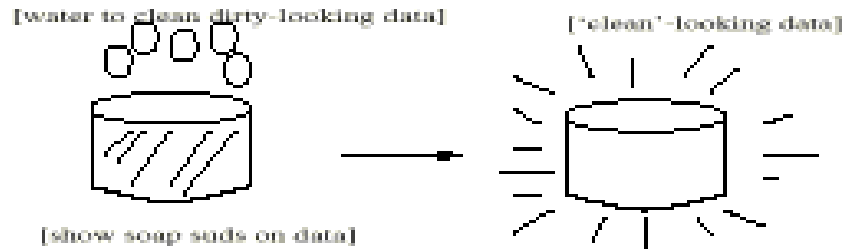
Major Tasks in Data Preprocessing



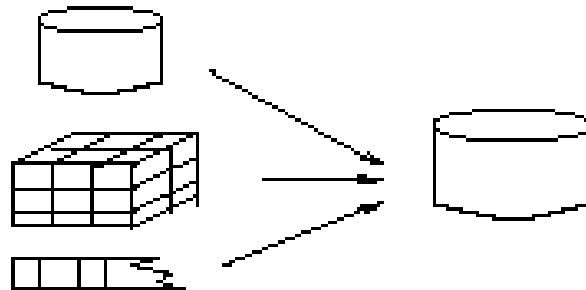
- Data cleaning
 - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- Data integration
 - Integration of multiple databases, data cubes, or files
- Data transformation
 - Normalization and aggregation
- Data reduction
 - Obtains reduced representation in volume but produces the same or similar analytical results
- Data discretization
 - Part of data reduction but with particular importance, especially for numerical data

Forms of Data Preprocessing

Data Cleaning



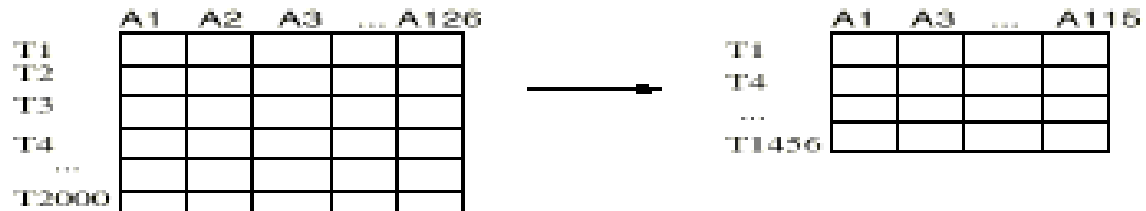
Data Integration



Data Transformation

-2, 32, 100, 59, 48 → -0.02, 0.32, 1.00, 0.59, 0.48

Data Reduction



Mining Data Descriptive Characteristics

- Motivation
 - To better understand the data: central tendency, variation and spread
- Data dispersion characteristics
 - median, max, min, quantiles, outliers, variance, etc.
- Numerical dimensions correspond to sorted intervals
 - Data dispersion: analyzed with multiple granularities of precision
 - Boxplot or quantile analysis on sorted intervals
- Dispersion analysis on computed measures
 - Folding measures into numerical dimensions
 - Boxplot or quantile analysis on the transformed cube

DATA PREPROCESSING

- Why preprocess the data?
- Descriptive data summarization
- Data cleaning
- Data integration and transformation
- Data reduction
- Discretization and concept hierarchy generation

Data Cleaning

- Importance
 - “Data cleaning is one of the three biggest problems in data warehousing” —Ralph Kimball
 - “Data cleaning is the number one problem in data warehousing” —DCI survey
- Data cleaning tasks
 - Fill in missing values
 - Identify outliers and smooth out noisy data
 - Correct inconsistent data
 - Resolve redundancy caused by data integration

Missing Data

- Data is not always available
 - E.g., many tuples have no recorded value for several attributes, such as customer income in sales data
- Missing data may be due to
 - equipment malfunction
 - inconsistent with other recorded data and thus deleted
 - data not entered due to misunderstanding
 - certain data may not be considered important at the time of entry
 - not register history or changes of the data
- Missing data may need to be inferred.

How to Handle Missing Data?

- Ignore the tuple: usually done when class label is missing (assuming the tasks in classification—not effective when the percentage of missing values per attribute varies considerably).
- Fill in the missing value manually: tedious + infeasible?
- Fill in it automatically with
 - a global constant : e.g., “unknown”, a new class?!
 - the attribute mean
 - the attribute mean for all samples belonging to the same class: smarter
 - the most probable value: inference-based such as Bayesian formula or decision tree

Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values may due to
 - faulty data collection instruments
 - data entry problems
 - data transmission problems
 - technology limitation
 - inconsistency in naming convention
- Other data problems which requires data cleaning
 - duplicate records
 - incomplete data
 - inconsistent data

How to Handle Noisy Data?

- **Binning**
 - first sort data and partition into (equal-frequency) bins
 - then one can **smooth by bin means**, **smooth by bin median**, **smooth by bin boundaries**, etc.
- **Regression**
 - smooth by fitting the data into regression functions
- **Clustering**
 - detect and remove outliers
- **Combined computer and human inspection**
 - detect suspicious values and check by human (e.g., deal with possible outliers)

Simple Discretization Methods: Binning



- **Equal-width** (distance) partitioning
 - Divides the range into N intervals of equal size: uniform grid
 - if A and B are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
 - The most straightforward, but outliers may dominate presentation
 - Skewed data is not handled well
- **Equal-depth** (frequency) partitioning
 - Divides the range into N intervals, each containing approximately same number of samples
 - Good data scaling
 - Managing categorical attributes can be tricky

Binning Methods for Data Smoothing

☐ Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

* Partition into equal-frequency (equi-depth) bins:

- Bin 1: 4, 8, 9, 15

- Bin 2: 21, 21, 24, 25

- Bin 3: 26, 28, 29, 34

* Smoothing by bin means:

- Bin 1: 9, 9, 9, 9

- Bin 2: 23, 23, 23, 23

- Bin 3: 29, 29, 29, 29

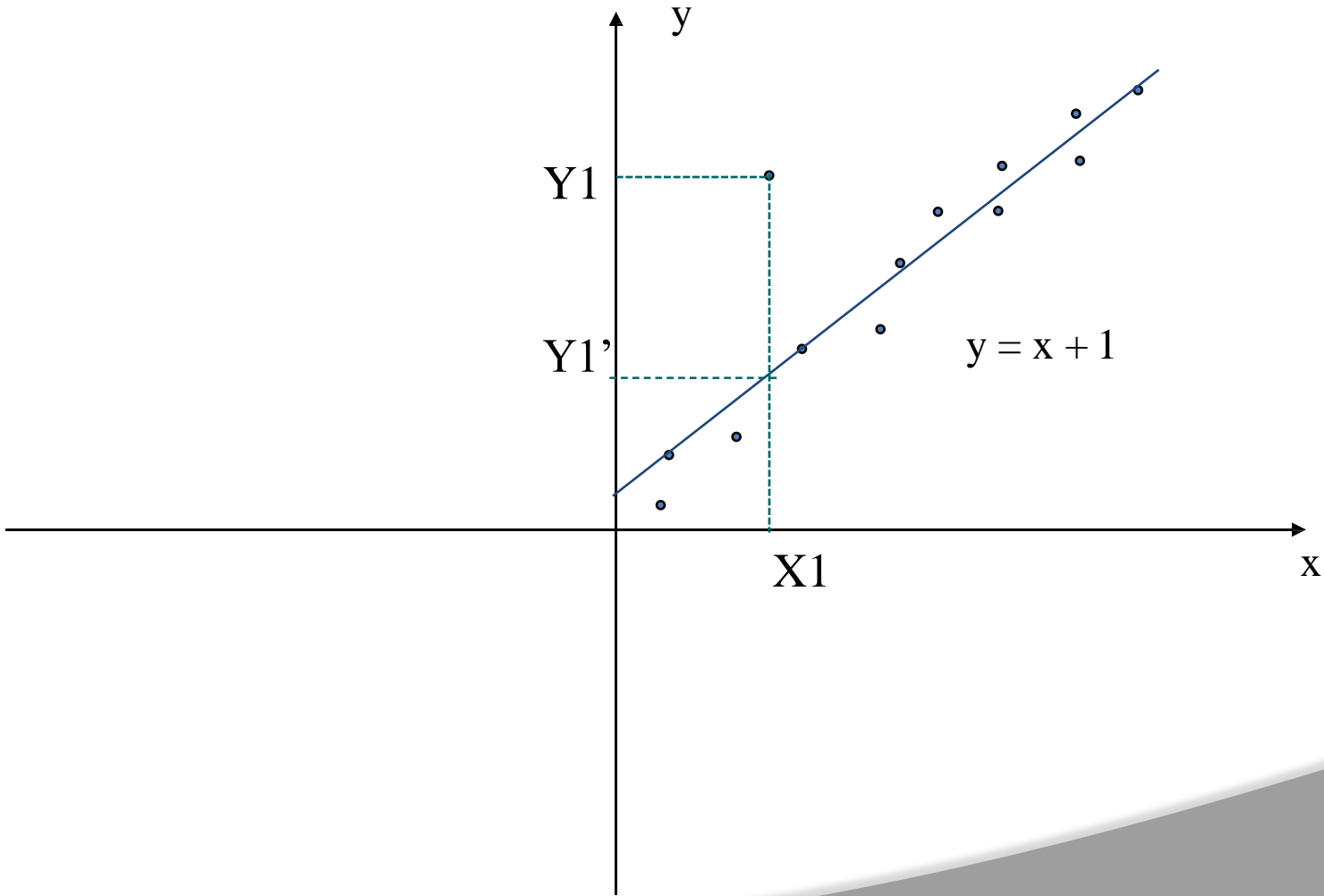
* Smoothing by bin boundaries:

- Bin 1: 4, 4, 4, 15

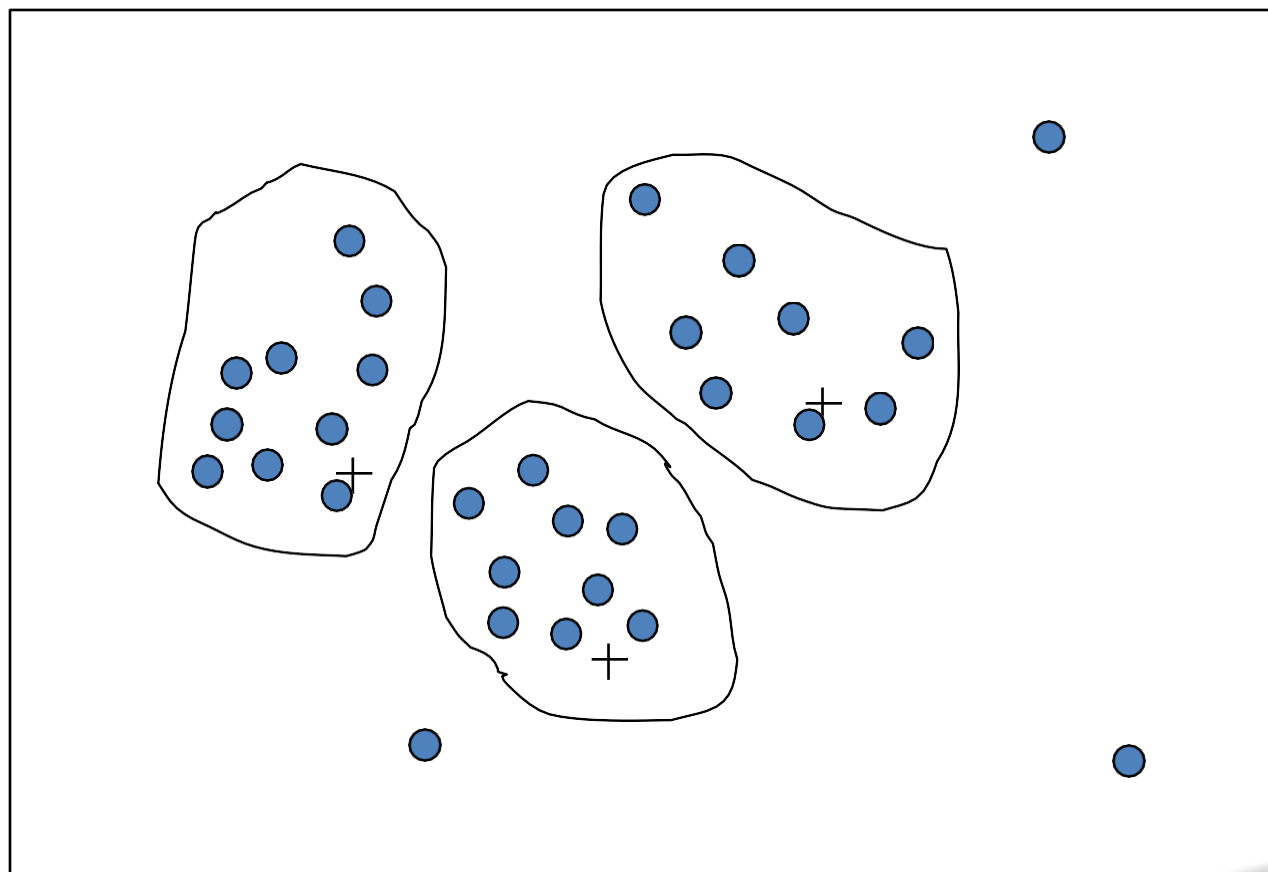
- Bin 2: 21, 21, 25, 25

- Bin 3: 26, 26, 26, 34

Regression



Cluster Analysis



Data Cleaning as a Process

- Data discrepancy detection
 - Use metadata (e.g., domain, range, dependency, distribution)
 - Check field overloading
 - Check uniqueness rule, consecutive rule and null rule
 - Use commercial tools
 - Data scrubbing: use simple domain knowledge (e.g., postal code, spell-check) to detect errors and make corrections
 - Data auditing: by analyzing data to discover rules and relationship to detect violators (e.g., correlation and clustering to find outliers)
- Data migration and integration
 - Data migration tools: allow transformations to be specified
 - ETL (Extraction/Transformation/Loading) tools: allow users to specify transformations through a graphical user interface
- Integration of the two processes
 - Iterative and interactive (e.g., Potter's Wheels)

Data Integration

- Data integration:
 - Combines data from multiple sources into a coherent store
- Schema integration: e.g., $A.cust-id \equiv B.cust-\#$
 - Integrate metadata from different sources
- **Entity identification problem:**
 - Identify real world entities from multiple data sources, e.g.,
Bill Clinton = William Clinton
- Detecting and resolving data value conflicts
 - For the same real world entity, attribute values from different sources are different
 - Possible reasons: different representations, different scales, e.g., metric vs. British units

Handling Redundancy in Data Integration



- Redundant data occur often when integration of multiple databases
 - *Object identification*: The same attribute or object may have different names in different databases
 - *Derivable data*: One attribute may be a “derived” attribute in another table, e.g., annual revenue
- Redundant attributes may be able to be detected by *correlation analysis*
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

Correlation Analysis (Numerical Data)

- Correlation coefficient (also called **Pearson's product moment coefficient**)

$$r_{A,B} = \frac{\sum (A - \bar{A})(B - \bar{B})}{(n - 1)\sigma_A \sigma_B} = \frac{\sum (AB) - n\bar{A}\bar{B}}{(n - 1)\sigma_A \sigma_B}$$

where n is the number of tuples, \bar{A} and \bar{B} are the respective means of A and B , σ_A and σ_B are the respective standard deviation of A and B , and $\sum(AB)$ is the sum of the AB cross-product.

- If $r_{A,B} > 0$, A and B are positively correlated (A 's values increase as B 's). The higher, the stronger correlation.
- $r_{A,B} = 0$: independent; $r_{A,B} < 0$: negatively correlated

Correlation Analysis (Categorical Data)

- χ^2 (chi-square) test

$$\chi^2 = \sum \frac{(\text{Observed} - \text{Expected})^2}{\text{Expected}}$$

- The larger the χ^2 value, the more likely the variables are related
- The cells that contribute the most to the χ^2 value are those whose actual count is very different from the expected count
- Correlation does not imply causality
 - # of hospitals and # of car-theft in a city are correlated
 - Both are causally linked to the third variable: population

Chi-Square Calculation: An Example

	Play chess	Not play chess	Sum (row)
Like science fiction	250(90)	200(360)	450
Not like science fiction	50(210)	1000(840)	1050
Sum(col.)	300	1200	1500

- χ^2 (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories)

$$\chi^2 = \frac{(250 - 90)^2}{90} + \frac{(50 - 210)^2}{210} + \frac{(200 - 360)^2}{360} + \frac{(1000 - 840)^2}{840} = 507.93$$

- It shows that like_science_fiction and play_chess are correlated in the group

Data Transformation

- Smoothing: remove noise from data
- Aggregation: summarization, data cube construction
- Generalization: concept hierarchy climbing
- Normalization: scaled to fall within a small, specified range
 - min-max normalization
 - z-score normalization
 - normalization by decimal scaling
- Attribute/feature construction
 - New attributes constructed from the given ones

Data Transformation: Normalization

- Min-max normalization: to $[new_min_A, new_max_A]$

$$v' = \frac{v - min_A}{max_A - min_A} (new_max_A - new_min_A) + new_min_A$$

- Ex. Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0].

Then \$73,000 is mapped to

$$\frac{73,600 - 12,000}{98,000 - 12,000} (1.0 - 0.0) + 0 = 0.716$$

- Z-score normalization (μ : mean, σ : standard deviation):

$$v' = \frac{v - \mu_A}{\sigma_A}$$

- Ex. Let $\mu = 54,000$, $\sigma = 16,000$. Then

$$\frac{73,600 - 54,000}{16,000} = 1.225$$

- Normalization by decimal scaling

$$v' = \frac{v}{10^j} \quad \text{Where } j \text{ is the smallest integer such that } \text{Max}(|v'|) < 1$$

Data Reduction Strategies

- Why data reduction?
 - A database/data warehouse may store terabytes of data
 - Complex data analysis/mining may take a very long time to run on the complete data set
- Data reduction
 - Obtain a reduced representation of the data set that is much smaller in volume but yet produce the same (or almost the same) analytical results
- Data reduction strategies
 - Data cube aggregation:
 - Dimensionality reduction — e.g., remove unimportant attributes
 - Data Compression
 - Numerosity reduction — e.g., fit data into models
 - Discretization and concept hierarchy generation

Data Cube Aggregation

- The lowest level of a data cube (base cuboid)
 - The aggregated data for an **individual entity of interest**
 - E.g., a customer in a phone calling data warehouse
- Multiple levels of aggregation in data cubes
 - Further reduce the size of data to deal with
- Reference appropriate levels
 - Use the smallest representation which is enough to solve the task
- Queries regarding aggregated information should be answered using data cube, when possible

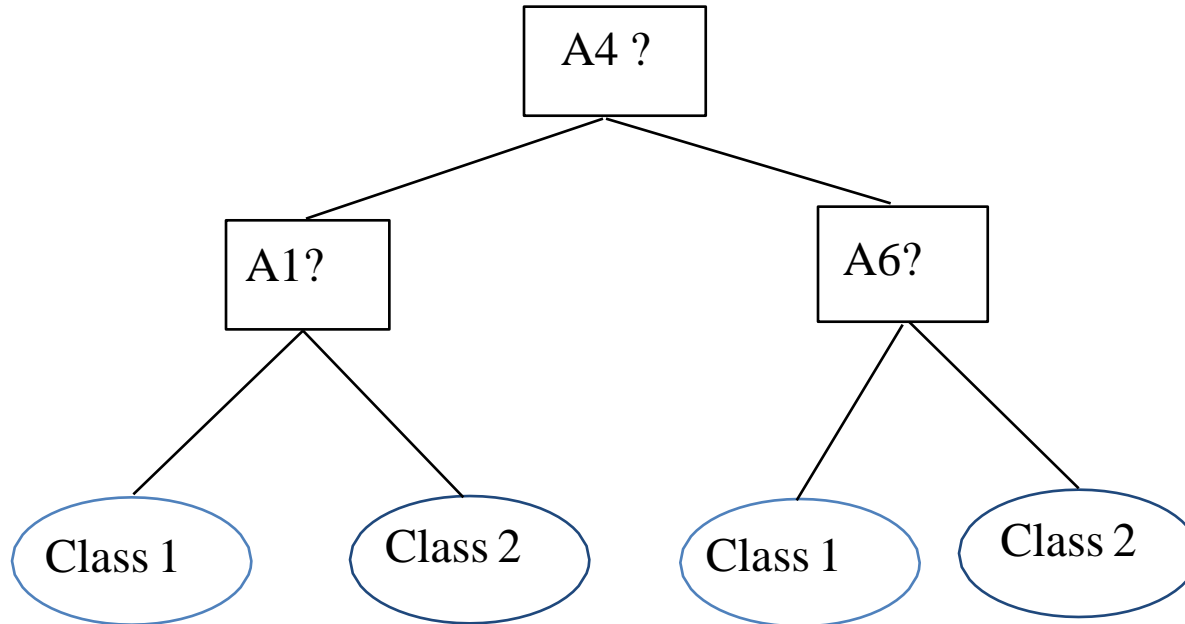
Attribute Subset Selection

- Feature selection (i.e., attribute subset selection):
 - Select a minimum set of features such that the probability distribution of different classes given the values for those features is as close as possible to the original distribution given the values of all features
 - reduce # of patterns in the patterns, easier to understand
- Heuristic methods (due to exponential # of choices):
 - Step-wise forward selection
 - Step-wise backward elimination
 - Combining forward selection and backward elimination
 - Decision-tree induction

Example of Decision Tree Induction

Initial attribute set:

{A1, A2, A3, A4, A5, A6}



-----> Reduced attribute set: {A1, A4, A6}

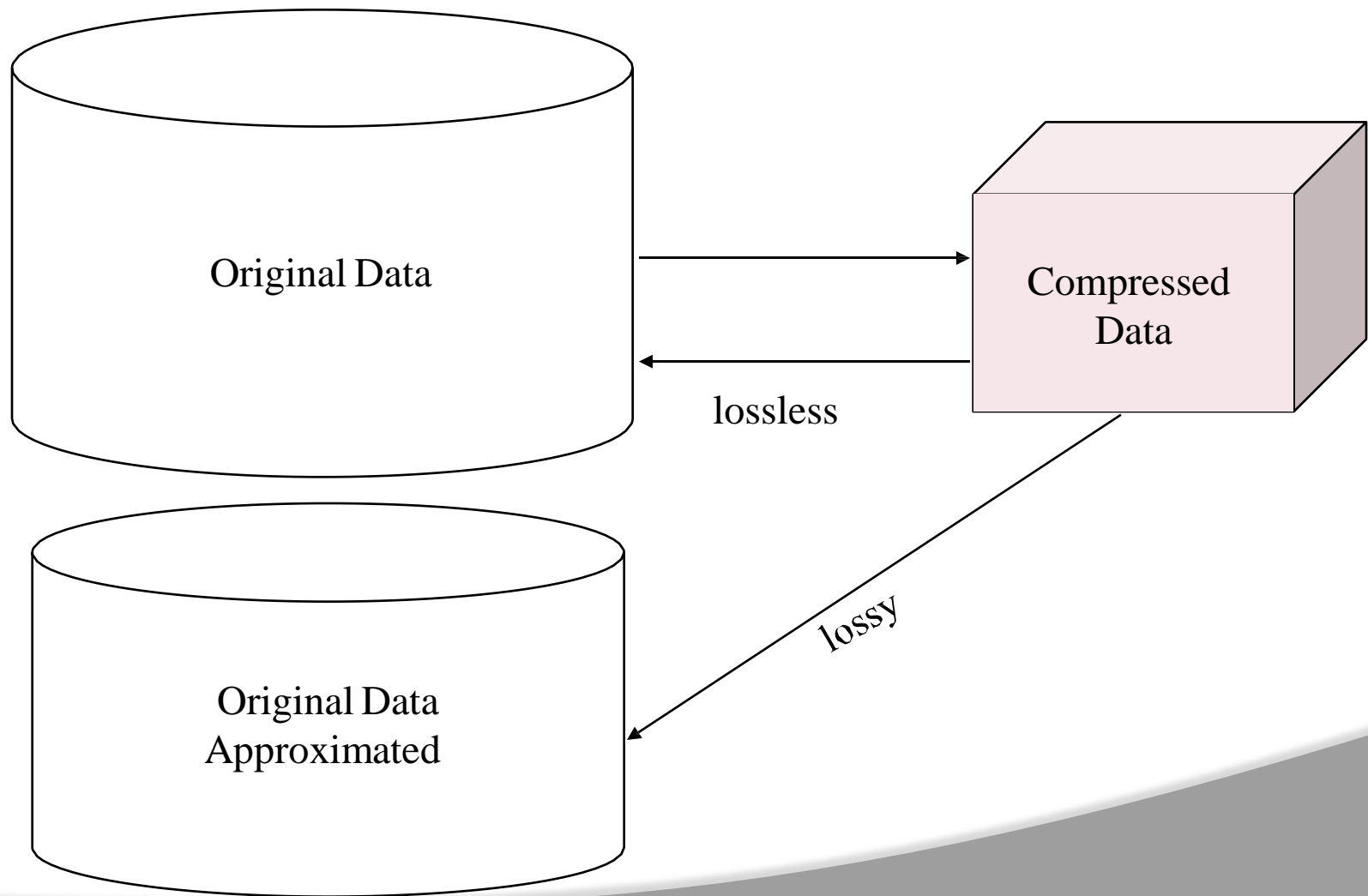
Heuristic Feature Selection Methods

- There are 2^d possible sub-features of d features
- Several heuristic feature selection methods:
 - Best single features under the feature independence assumption: choose by significance tests
 - Best step-wise feature selection:
 - The best single-feature is picked first
 - Then next best feature condition to the first, ...
 - Step-wise feature elimination:
 - Repeatedly eliminate the worst feature
 - Best combined feature selection and elimination
 - Optimal branch and bound:
 - Use feature elimination and backtracking

Data Compression

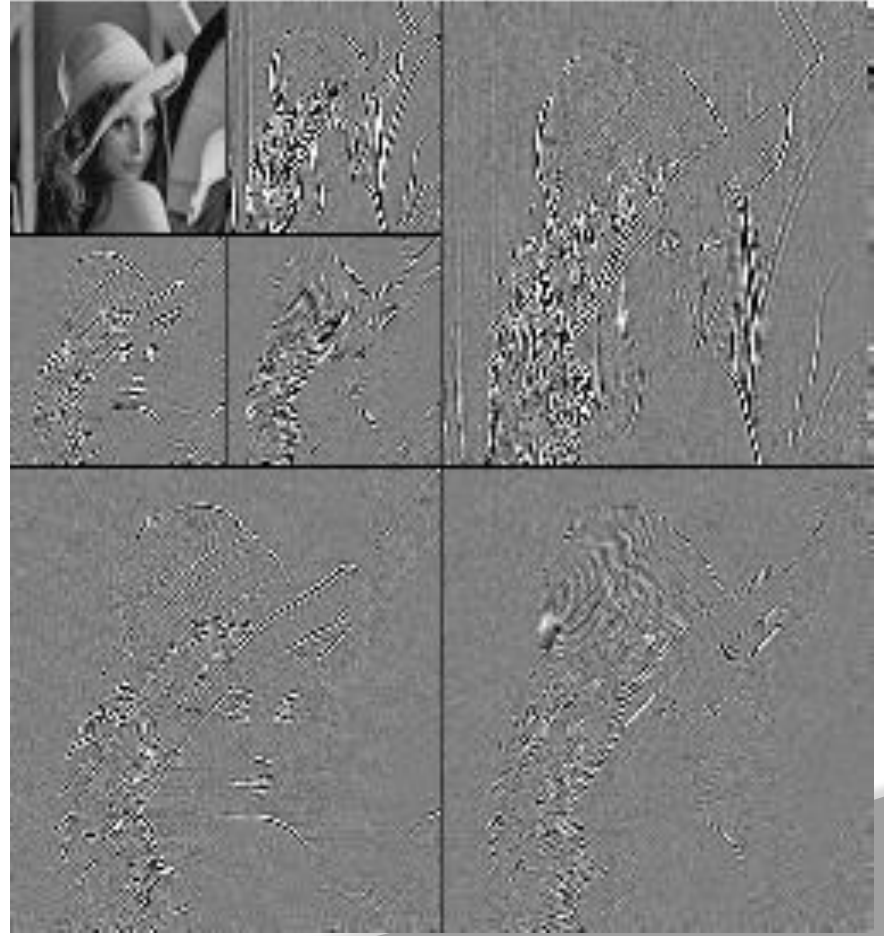
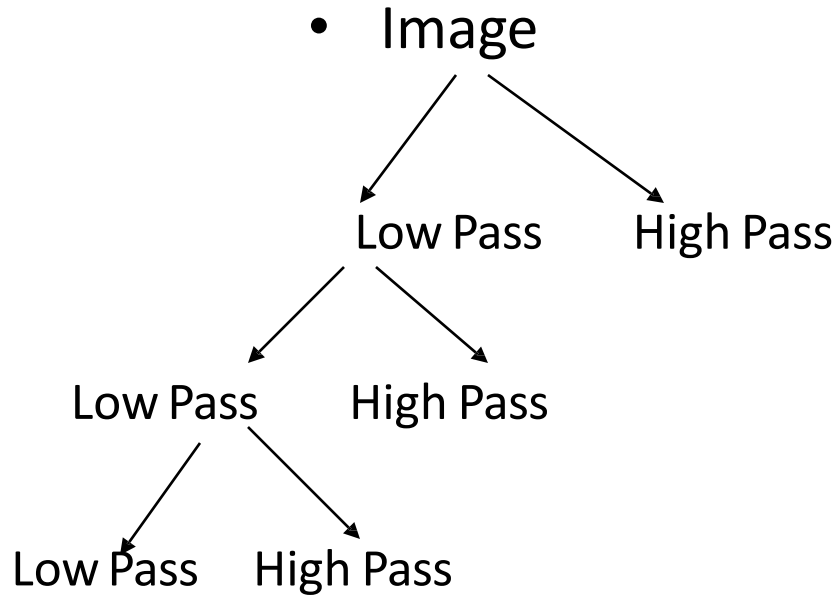
- String compression
 - There are extensive theories and well-tuned algorithms
 - Typically lossless
 - But only limited manipulation is possible without expansion
- Audio/video compression
 - Typically lossy compression, with progressive refinement
 - Sometimes small fragments of signal can be reconstructed without reconstructing the whole
- Time sequence is not audio
 - Typically short and vary slowly with time

Data Compression



- Discrete wavelet transform (DWT): linear signal processing, multi-resolutional analysis
- Compressed approximation: store only a small fraction of the strongest of the wavelet coefficients
- Similar to discrete Fourier transform (DFT), but better lossy compression, localized in space
- Method:
 - Length, L , must be an integer power of 2 (padding with 0's, when necessary)
 - Each transform has 2 functions: smoothing, difference
 - Applies to pairs of data, resulting in two set of data of length $L/2$
 - Applies two functions recursively, until reaches the desired length

DWT for Image Compression

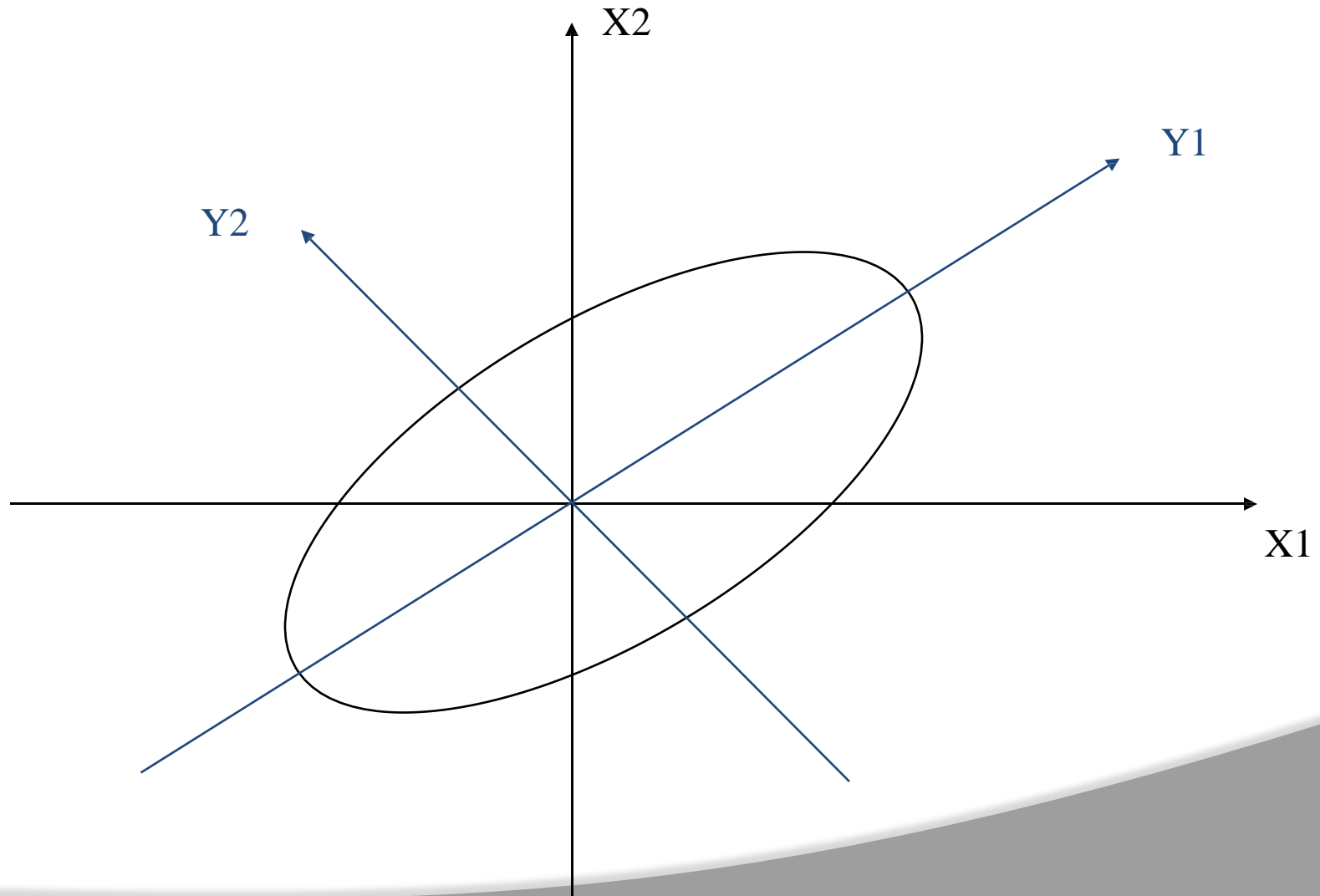


Dimensionality Reduction:

Principal Component Analysis (PCA)

- Given N data vectors from n -dimensions, find $k \leq n$ orthogonal vectors (*principal components*) that can be best used to represent data
- Steps
 - Normalize input data: Each attribute falls within the same range
 - Compute k orthonormal (unit) vectors, i.e., *principal components*
 - Each input data (vector) is a linear combination of the k principal component vectors
 - The principal components are sorted in order of decreasing “significance” or strength
 - Since the components are sorted, the size of the data can be reduced by eliminating the weak components, i.e., those with low variance. (i.e., using the strongest principal components, it is possible to reconstruct a good approximation of the original data)
- Works for numeric data only
- Used when the number of dimensions is large

Principal Component Analysis



Numerosity Reduction

- Reduce data volume by choosing alternative, smaller forms of data representation
- Parametric methods
 - Assume the data fits some model, estimate model parameters, store only the parameters, and discard the data (except possible outliers)
 - Example: Log-linear models—obtain value at a point in m - D space as the product on appropriate marginal subspaces
- Non-parametric methods
 - Do not assume models
 - Major families: histograms, clustering, sampling

Data Reduction Method (1): Regression and Log-Linear Models



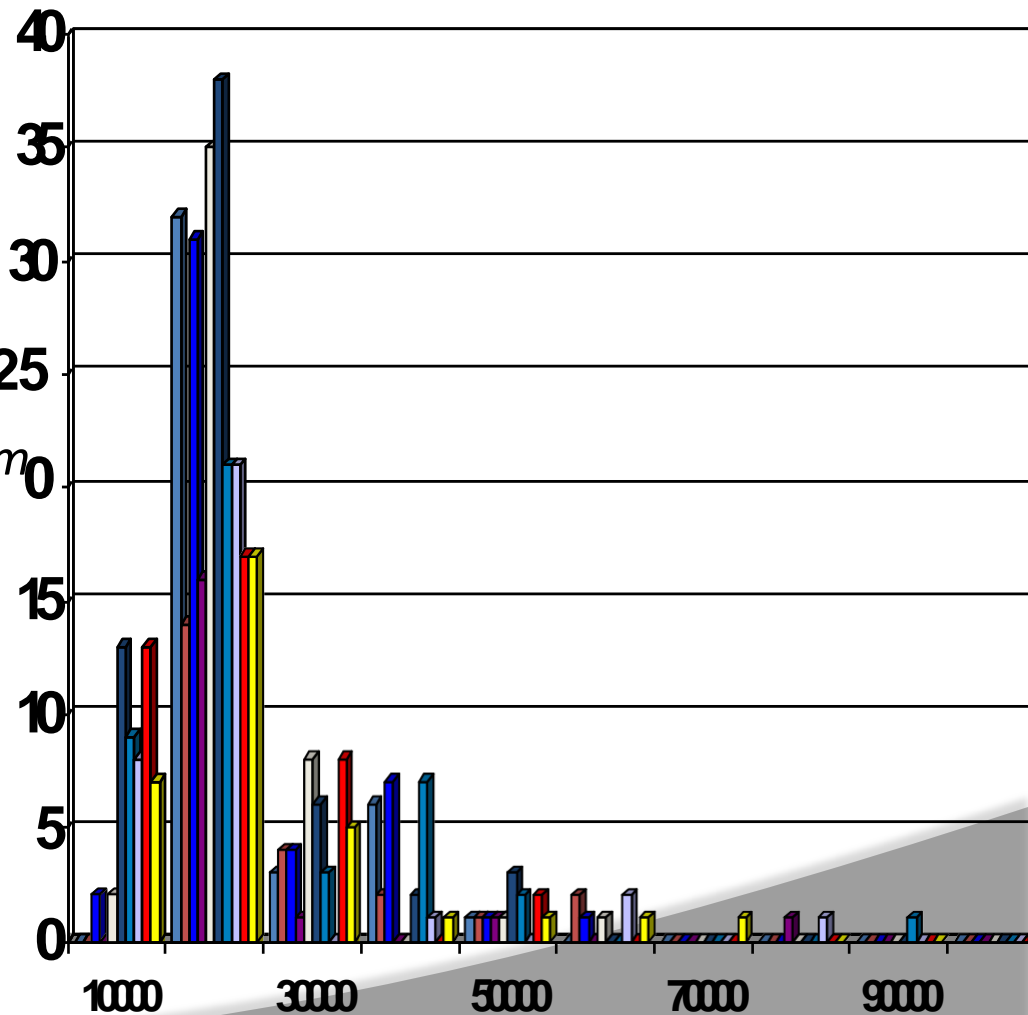
- Linear regression: Data are modeled to fit a straight line
 - Often uses the least-square method to fit the line
- Multiple regression: allows a response variable Y to be modeled as a linear function of multidimensional feature vector
- Log-linear model: approximates discrete multidimensional probability distributions

Regress Analysis and Log-Linear Models

- Linear regression: $Y = w X + b$
 - Two regression coefficients, w and b , specify the line and are to be estimated by using the data at hand
 - Using the least squares criterion to the known values of $Y_1, Y_2, \dots, X_1, X_2, \dots$
- Multiple regression: $Y = b_0 + b_1 X_1 + b_2 X_2$.
 - Many nonlinear functions can be transformed into the above
- Log-linear models:
 - The multi-way table of joint probabilities is approximated by a product of lower-order tables
 - Probability: $p(a, b, c, d) = \alpha_{ab} \beta_{ac} \chi_{ad} \delta_{bcd}$

Data Reduction Method (2):

- Divide data into buckets and store average (sum) for each bucket
- Partitioning rules:
 - Equal-width: equal bucket range
 - Equal-frequency (or equal-depth)
 - V-optimal: with the least *histogram variance* (weighted sum of the original values that each bucket represents)
 - MaxDiff: set bucket boundary between each pair for pairs have the $\beta-1$ largest differences



Data Reduction Method (3): Clustering

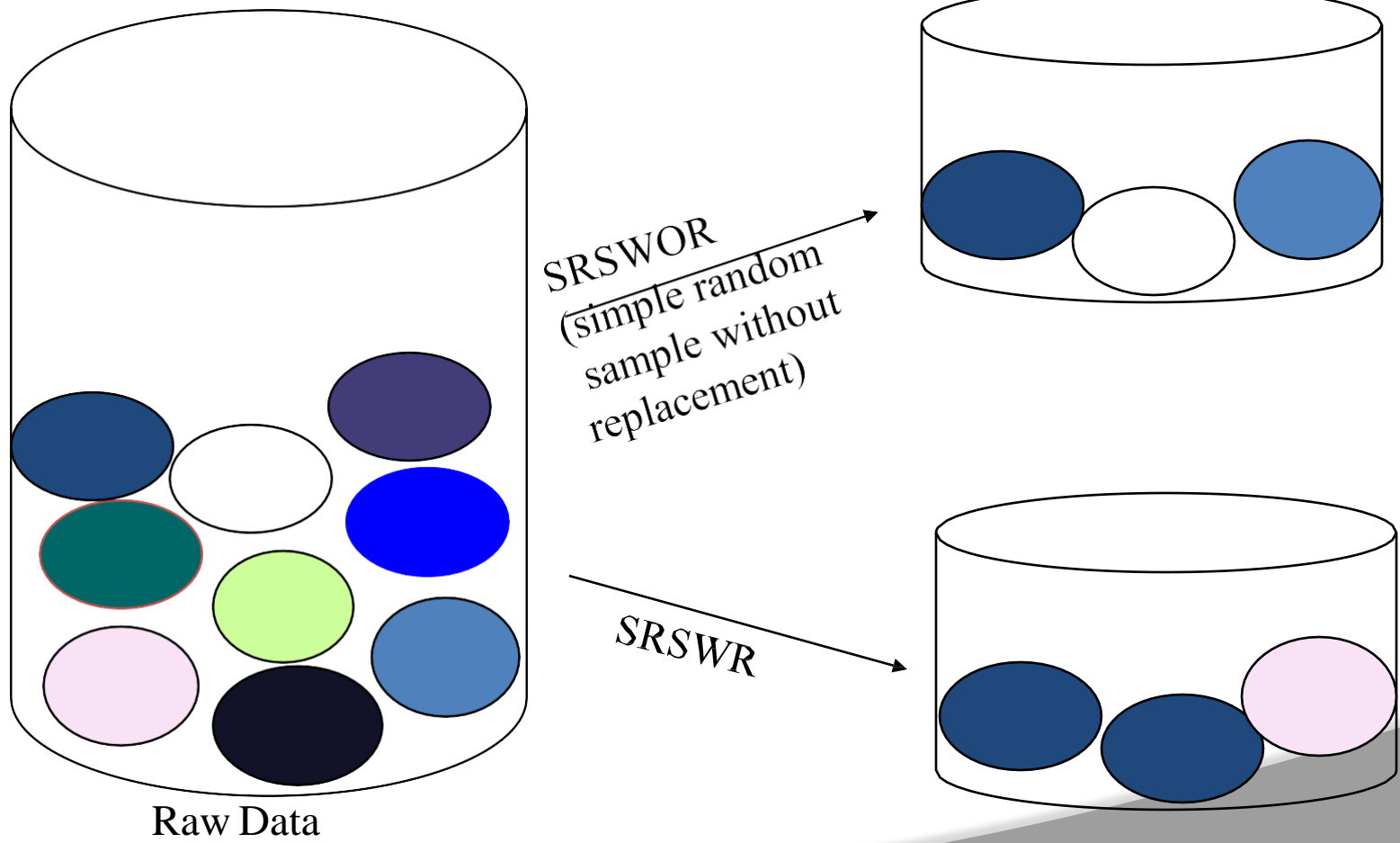
- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only
- Can be very effective if data is clustered but not if data is “smeared”
- Can have hierarchical clustering and be stored in multi-dimensional index tree structures
- There are many choices of clustering definitions and clustering algorithms
- Cluster analysis will be studied in depth in Chapter 7

Data Reduction Method (4): Sampling



- Sampling: obtaining a small sample s to represent the whole data set N
- Allow a mining algorithm to run in complexity that is potentially sub-linear to the size of the data
- Choose a **representative** subset of the data
 - Simple random sampling may have very poor performance in the presence of skew
- Develop adaptive sampling methods
 - Stratified sampling:
 - Approximate the percentage of each class (or subpopulation of interest) in the overall database
 - Used in conjunction with skewed data
- Note: Sampling may not reduce database I/Os (page at a time)

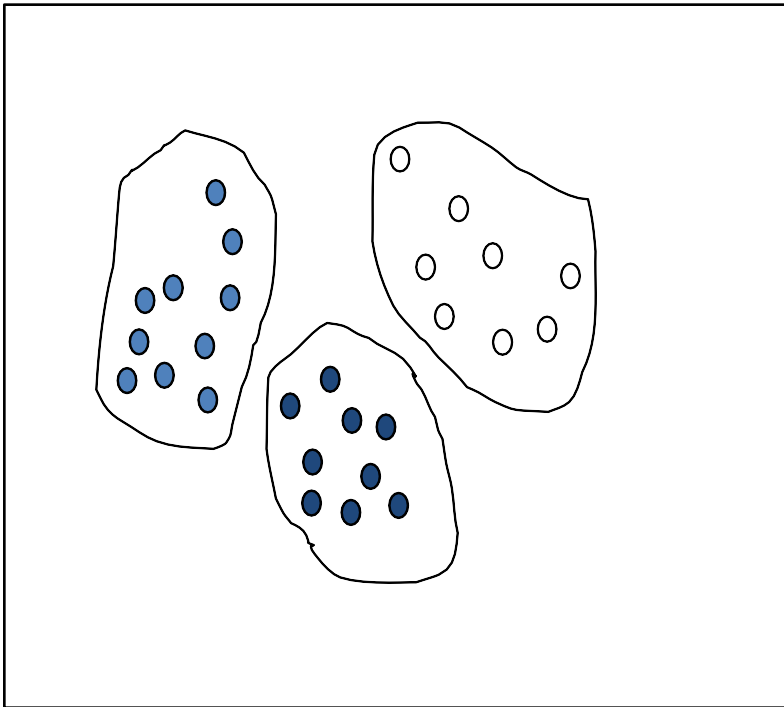
Sampling: with or without Replacement



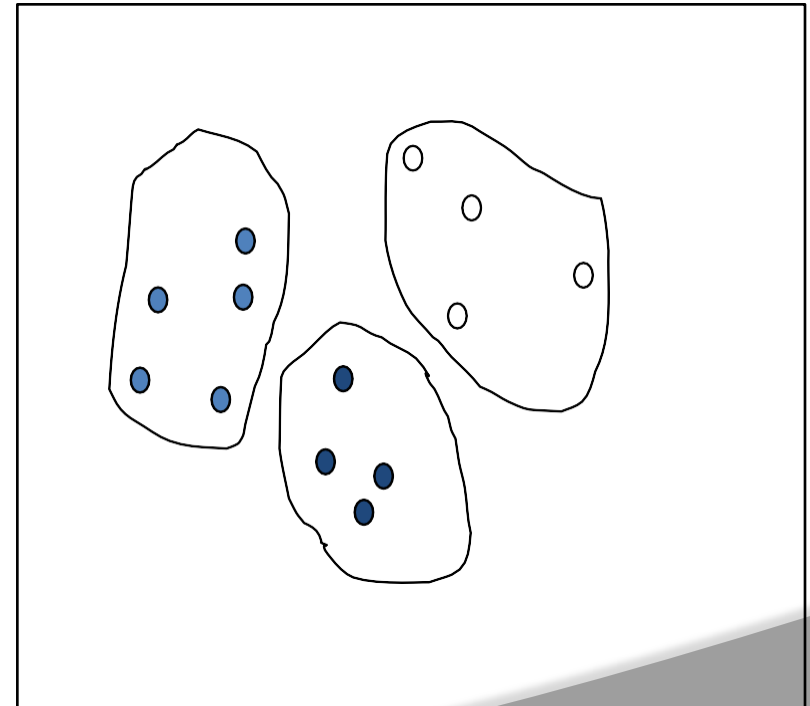
Raw Data

Sampling: Cluster or Stratified Sampling

Raw Data



Cluster/Stratified Sample



Discretization

- Three types of attributes:
 - Nominal — values from an unordered set, e.g., color, profession
 - Ordinal — values from an ordered set, e.g., military or academic rank
 - Continuous — real numbers, e.g., integer or real numbers
- Discretization:
 - Divide the range of a continuous attribute into intervals
 - Some classification algorithms only accept categorical attributes.
 - Reduce data size by discretization
 - Prepare for further analysis

Discretization and Concept Hierarchy

- Discretization
 - Reduce the number of values for a given continuous attribute by dividing the range of the attribute into intervals
 - Interval labels can then be used to replace actual data values
 - Supervised vs. unsupervised
 - Split (top-down) vs. merge (bottom-up)
 - Discretization can be performed recursively on an attribute
- Concept hierarchy formation
 - Recursively reduce the data by collecting and replacing low level concepts (such as numeric values for age) by higher level concepts (such as young, middle-aged, or senior)

Discretization and Concept Hierarchy Generation for Numeric Data



- Typical methods: All the methods can be applied recursively
 - Binning (covered above)
 - Top-down split, unsupervised,
 - Histogram analysis (covered above)
 - Top-down split, unsupervised
 - Clustering analysis (covered above)
 - Either top-down split or bottom-up merge, unsupervised
 - Entropy-based discretization: supervised, top-down split
 - Interval merging by χ^2 Analysis: unsupervised, bottom-up merge
 - Segmentation by natural partitioning: top-down split, unsupervised

Entropy-Based Discretization

- Given a set of samples S , if S is partitioned into two intervals S_1 and S_2 using boundary T , the information gain after partitioning is

$$I(S, T) = \frac{|S_1|}{|S|} \text{Entropy}(S_1) + \frac{|S_2|}{|S|} \text{Entropy}(S_2)$$

- Entropy is calculated based on class distribution of the samples in the set. Given m classes, the entropy of S_1 is

$$\text{Entropy}(S_1) = - \sum_{i=1}^m p_i \log_2(p_i)$$

where p_i is the probability of class i in S_1

- The boundary that minimizes the entropy function over all possible boundaries is selected as a binary discretization
- The process is recursively applied to partitions obtained until some stopping criterion is met
- Such a boundary may reduce data size and improve classification accuracy

Interval Merge by χ^2 Analysis

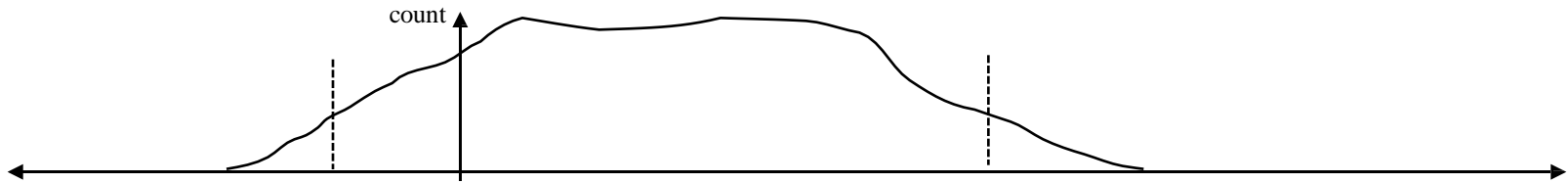
- Merging-based (bottom-up) vs. splitting-based methods
- Merge: Find the best neighboring intervals and merge them to form larger intervals recursively
- ChiMerge [Kerber AAAI 1992, See also Liu et al. DMKD 2002]
 - Initially, each distinct value of a numerical attr. A is considered to be one interval
 - χ^2 tests are performed for every pair of adjacent intervals
 - Adjacent intervals with the least χ^2 values are merged together, since low χ^2 values for a pair indicate similar class distributions
 - This merge process proceeds recursively until a predefined stopping criterion is met (such as significance level, max-interval, max inconsistency, etc.)

Segmentation by Natural Partitioning



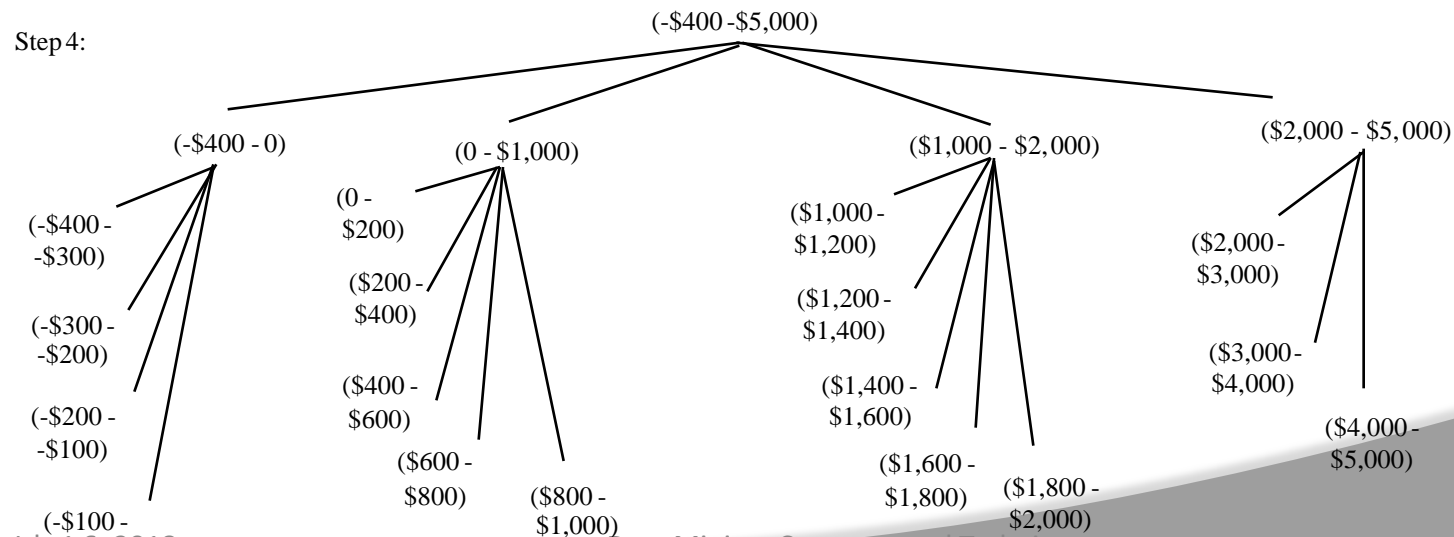
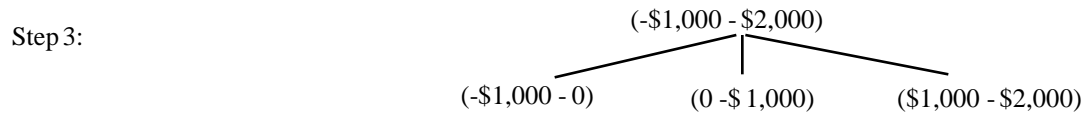
- A simply 3-4-5 rule can be used to segment numeric data into relatively uniform, “natural” intervals.
 - If an interval covers 3, 6, 7 or 9 distinct values at the most significant digit, partition the range into 3 equi-width intervals
 - If it covers 2, 4, or 8 distinct values at the most significant digit, partition the range into 4 intervals
 - If it covers 1, 5, or 10 distinct values at the most significant digit, partition the range into 5 intervals

Example of 3-4-5 Rule



Step 1: -\$351 -\$159 profit \$1,838 \$4,700
 Min Low (i.e, 5%-tile) High(i.e, 95%-tile) Max

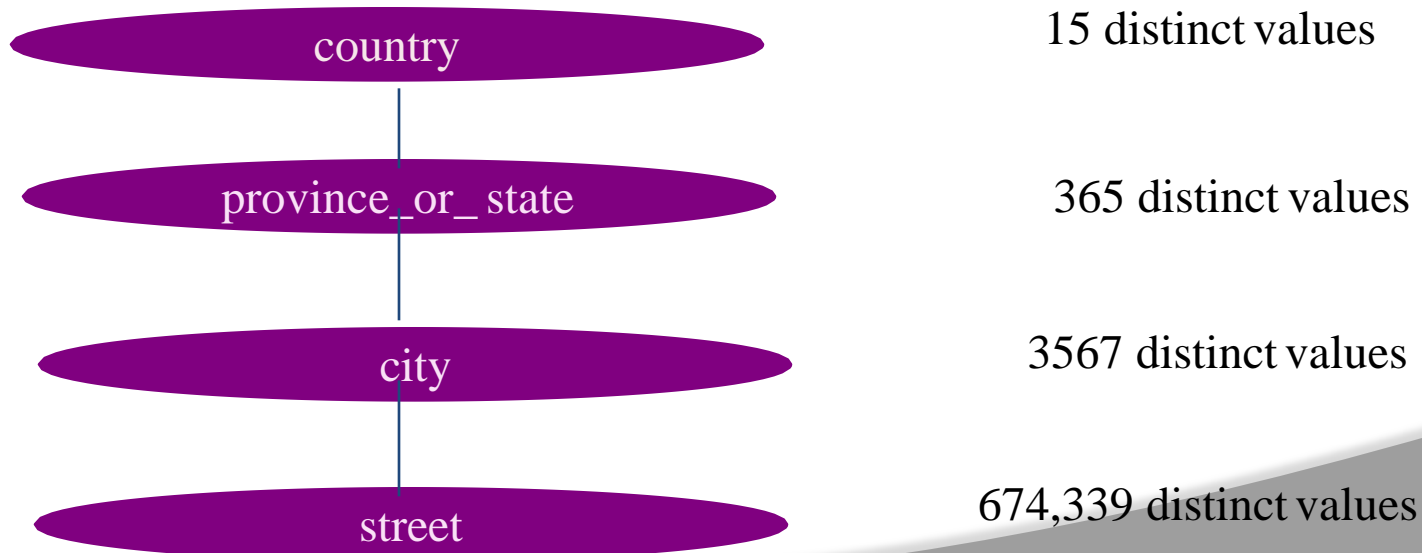
Step 2: msd=1,000 Low=-\$1,000 High=\$2,000



- Specification of a partial/total ordering of attributes explicitly at the schema level by users or experts
 - street < city < state < country
- Specification of a hierarchy for a set of values by explicit data grouping
 - {Urbana, Champaign, Chicago} < Illinois
- Specification of only a partial set of attributes
 - E.g., only street < city, not others
- Automatic generation of hierarchies (or attribute levels) by the analysis of the number of distinct values
 - E.g., for a set of attributes: {street, city, state, country}

Automatic Concept Hierarchy Generation

- Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set
 - The attribute with the most distinct values is placed at the lowest level of the hierarchy
 - Exceptions, e.g., weekday, month, quarter, year





MODULE– III

ASSOCIATION RULE MINING

CLOs	Course Learning Outcome
CLO9	Illustrate the concept of Apriori algorithm for finding frequent items and generating association rules. Association rules.
CLO10	Illustrate the concept of Fp-growth algorithm and different representations of frequent item sets.
CLO11	Understand the classification problem and Prediction
CLO12	Explore on decision tree construction and attribute selection

What Is Frequent Pattern

Analysis?



- Frequent pattern: a pattern (a set of items, subsequences, substructures, etc.) that occurs frequently in a data set
- First proposed by Agrawal, Imielinski, and Swami [AIS93] in the context of frequent itemsets and association rule mining
- Motivation: Finding inherent regularities in data
 - What products were often purchased together?— Beer and diapers?!
 - What are the subsequent purchases after buying a PC?
 - What kinds of DNA are sensitive to this new drug?
 - Can we automatically classify web documents?
- Applications
 - Basket data analysis, cross-marketing, catalog design, sale campaign analysis, Web log (click stream) analysis, and DNA sequence analysis.

Why Is Freq. Pattern Mining Important?

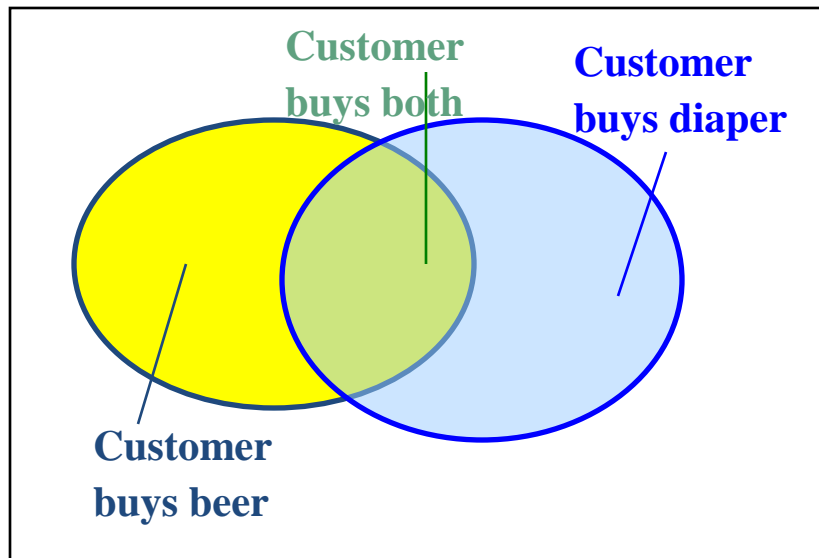
- Discloses an intrinsic and important property of data sets
- Forms the foundation for many essential data mining tasks
 - Association, correlation, and causality analysis
 - Sequential, structural (e.g., sub-graph) patterns
 - Pattern analysis in spatiotemporal, multimedia, time-series, and stream data
 - Classification: associative classification
 - Cluster analysis: frequent pattern-based clustering
 - Data warehousing: iceberg cube and cube-gradient
 - Semantic data compression: fascicles
 - Broad applications

Basic Concepts: Frequent Patterns and Association Rules

Rules

Transaction-id	Items bought
10	A, B, D
20	A, C, D
30	A, D, E
40	B, E, F
50	B, C, D, E, F

- Itemset $X = \{x_1, \dots, x_k\}$
- Find all the rules $X \rightarrow Y$ with minimum support and confidence
 - support, s , probability that a transaction contains $X \cup Y$
 - confidence, c , conditional probability that a transaction having X also contains Y



Let $sup_{min} = 50\%$, $conf_{min} = 50\%$
 Freq. Pat.: $\{A:3, B:3, D:4, E:3, AD:3\}$

Association rules:

$A \rightarrow D$ (60%, 100%)

$D \rightarrow A$ (60%, 75%)

Closed Patterns and Max-Patterns

- A long pattern contains a combinatorial number of sub-patterns, e.g., $\{a_1, \dots, a_{100}\}$ contains $\binom{100}{1} + \binom{100}{2} + \dots + \binom{100}{100} = 2^{100} - 1 = 1.27 \cdot 10^{30}$ sub-patterns!
- Solution: *Mine closed patterns and max-patterns instead*
- An itemset X is closed if X is *frequent* and there exists *no super-pattern* $Y \supset X$, with the same support as X (proposed by Pasquier, et al. @ ICDT'99)
- An itemset X is a max-pattern if X is frequent and there exists no frequent super-pattern $Y \supset X$ (proposed by Bayardo @ SIGMOD'98)
- Closed pattern is a lossless compression of freq. patterns
 - Reducing the # of patterns and rules

Closed Patterns and Max-Pattern

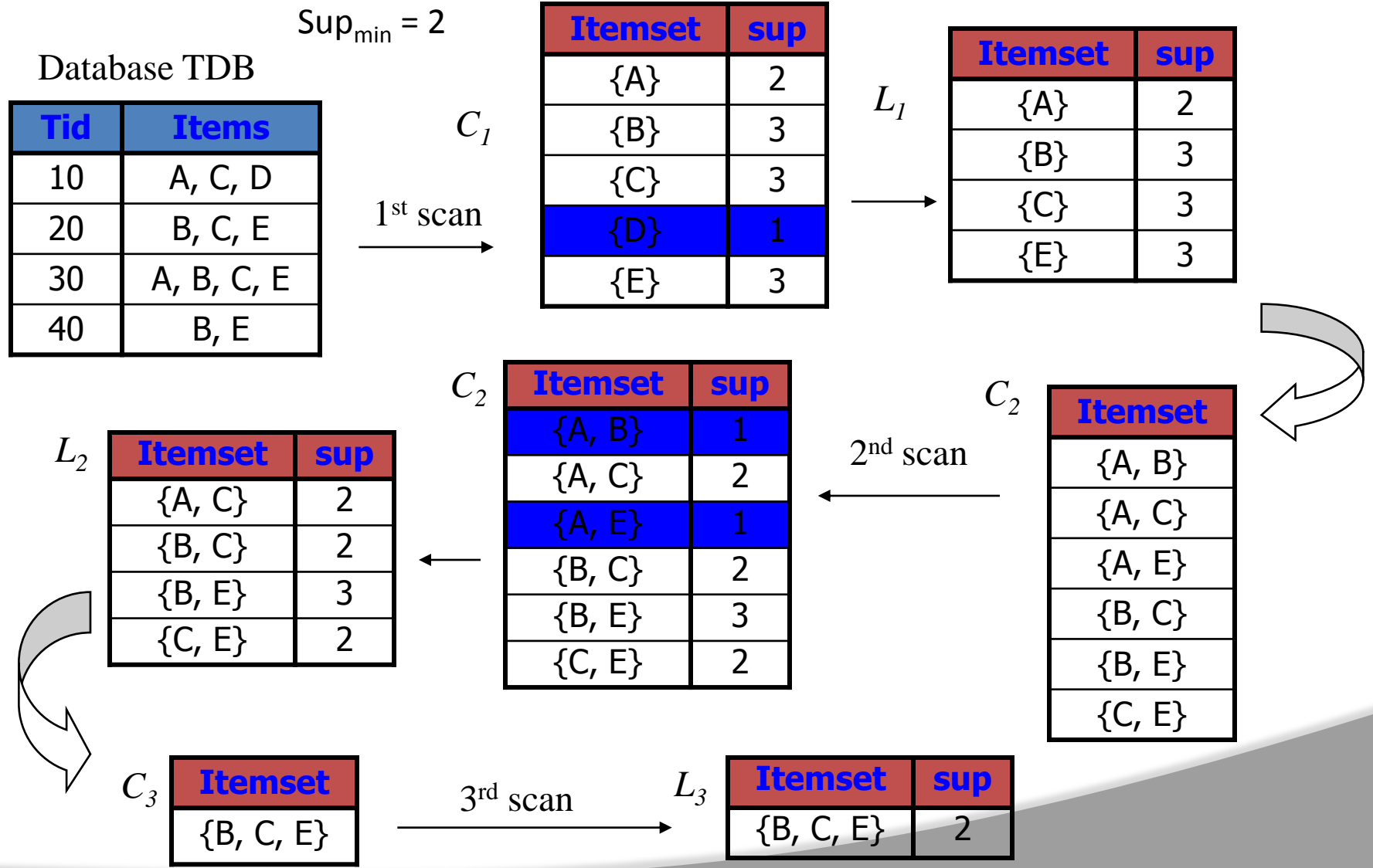
- Exercise. $DB = \{ \langle a_1, \dots, a_{100} \rangle, \langle a_1, \dots, a_{50} \rangle \}$
 - $Min_sup = 1$.
- What is the set of closed itemset?
 - $\langle a_1, \dots, a_{100} \rangle: 1$
 - $\langle a_1, \dots, a_{50} \rangle: 2$
- What is the set of max-pattern?
 - $\langle a_1, \dots, a_{100} \rangle: 1$
- What is the set of all patterns?
 - !!

Scalable Methods for Mining Frequent Patterns

- The downward closure property of frequent patterns
 - Any subset of a frequent itemset must be frequent
 - If **{beer, diaper, nuts}** is frequent, so is **{beer, diaper}**
 - i.e., every transaction having {beer, diaper, nuts} also contains {beer, diaper}
- Scalable mining methods: Three major approaches
 - Apriori (Agrawal & Srikant@VLDB'94)
 - Freq. pattern growth (FPgrowth—Han, Pei & Yin @SIGMOD'00)
 - Vertical data format approach (Charm—Zaki & Hsiao @SDM'02)

- Apriori pruning principle: If there is any itemset which is infrequent, its superset should not be generated/tested! (Agrawal & Srikant @VLDB'94, Mannila, et al. @ KDD' 94)
- Method:
 - Initially, scan DB once to get frequent 1-itemset
 - Generate length $(k+1)$ candidate itemsets from length k frequent itemsets
 - Test the candidates against DB
 - Terminate when no frequent or candidate set can be generated

The Apriori Algorithm—An Example



The Apriori Algorithm

- Pseudo-code:

C_k : Candidate itemset of size k

L_k : frequent itemset of size k

$L_1 = \{\text{frequent items}\};$

for ($k = 1; L_k \neq \emptyset; k++$) **do begin**

C_{k+1} = candidates generated from L_k ;

for each transaction t in database do

 increment the count of all candidates in C_{k+1}

 that are contained in t

L_{k+1} = candidates in C_{k+1} with min_support

end

return $\cup_k L_k$;

Important Details of Apriori

- How to generate candidates?
 - Step 1: self-joining L_k
 - Step 2: pruning
- How to count supports of candidates?
- Example of Candidate-generation
 - $L_3 = \{abc, abd, acd, ace, bcd\}$
 - Self-joining: $L_3 * L_3$
 - $abcd$ from abc and abd
 - $acde$ from acd and ace
 - Pruning:
 - $acde$ is removed because ade is not in L_3
 - $C_4 = \{abcd\}$

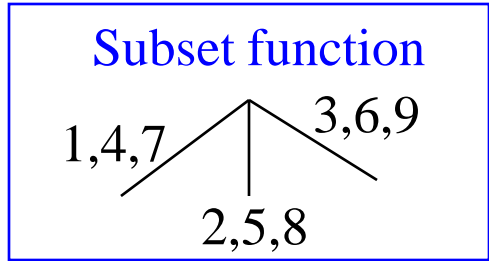
How to Generate Candidates?

- Suppose the items in L_{k-1} are listed in an order
- Step 1: self-joining L_{k-1}
 insert into C_k
 select $p.item_1, p.item_2, \dots, p.item_{k-1}, q.item_{k-1}$
 from $L_{k-1} p, L_{k-1} q$
 where $p.item_1=q.item_1, \dots, p.item_{k-2}=q.item_{k-2}, p.item_{k-1} < q.item_{k-1}$
- Step 2: pruning
 forall *itemsets* c in C_k do
 forall *(k-1)-subsets* s of c do
 if (s is not in L_{k-1}) **then delete** c from C_k

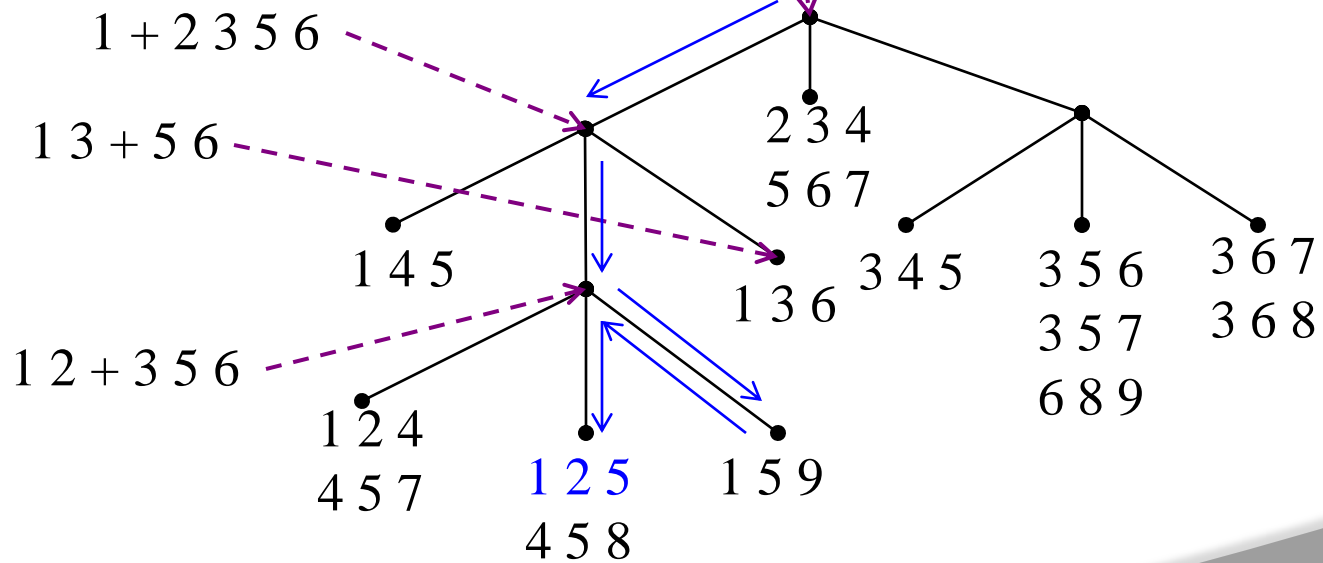
How to Count Supports of Candidates?

- Why counting supports of candidates a problem?
 - The total number of candidates can be very huge
 - One transaction may contain many candidates
- Method:
 - Candidate itemsets are stored in a *hash-tree*
 - *Leaf* node of hash-tree contains a list of itemsets and counts
 - *Interior* node contains a hash table
 - *Subset function*: finds all the candidates contained in a transaction

Example: Counting Supports of Candidates



Transaction: 1 2 3 5 6



Efficient Implementation of Apriori in SQL

- Hard to get good performance out of pure SQL (SQL-92) based approaches alone
- Make use of object-relational extensions like UDFs, BLOBs, Table functions etc.
 - Get orders of magnitude improvement
- S. Sarawagi, S. Thomas, and R. Agrawal. Integrating association rule mining with relational database systems: Alternatives and implications. In SIGMOD'98

Challenges of Frequent Pattern Mining

- Challenges
 - Multiple scans of transaction database
 - Huge number of candidates
 - Tedious workload of support counting for candidates
- Improving Apriori: general ideas
 - Reduce passes of transaction database scans
 - Shrink number of candidates
 - Facilitate support counting of candidates

Partition: Scan Database Only Twice

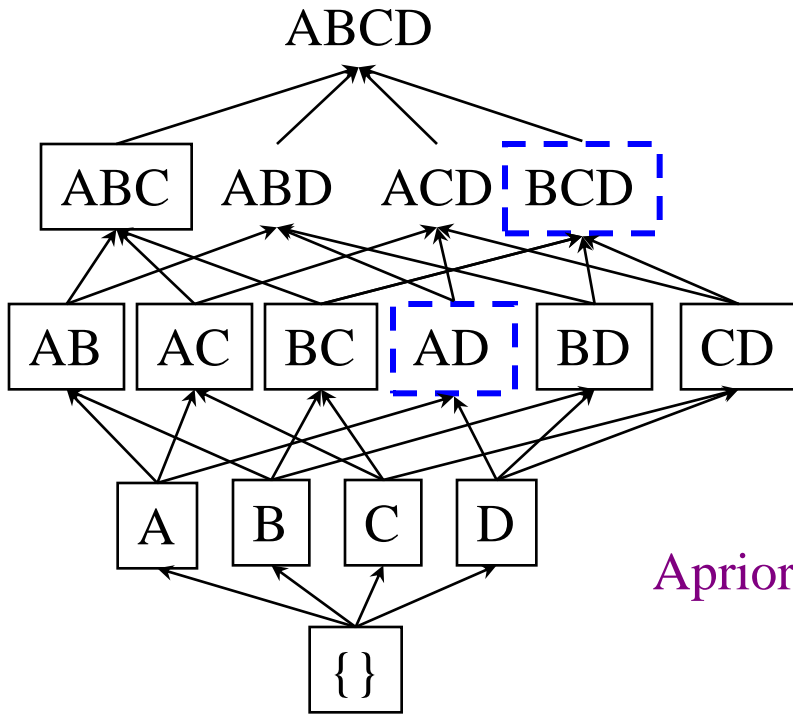
- Any itemset that is potentially frequent in DB must be frequent in at least one of the partitions of DB
 - Scan 1: partition database and find local frequent patterns
 - Scan 2: consolidate global frequent patterns
- A. Savasere, E. Omiecinski, and S. Navathe. An efficient algorithm for mining association in large databases. In *VLDB'95*

- A k -itemset whose corresponding hashing bucket count is below the threshold cannot be frequent
 - Candidates: a, b, c, d, e
 - Hash entries: {ab, ad, ae} {bd, be, de} ...
 - Frequent 1-itemset: a, b, d, e
 - ab is not a candidate 2-itemset if the sum of count of {ab, ad, ae} is below support threshold
- J. Park, M. Chen, and P. Yu. An effective hash-based algorithm for mining association rules. In *SIGMOD'95*

Sampling for Frequent Patterns

- Select a sample of original database, mine frequent patterns within sample using Apriori
- Scan database once to verify frequent itemsets found in sample, only *borders* of closure of frequent patterns are checked
 - Example: check *abcd* instead of *ab, ac, ..., etc.*
- Scan database again to find missed frequent patterns
- H. Toivonen. Sampling large databases for association rules. In *VLDB'96*

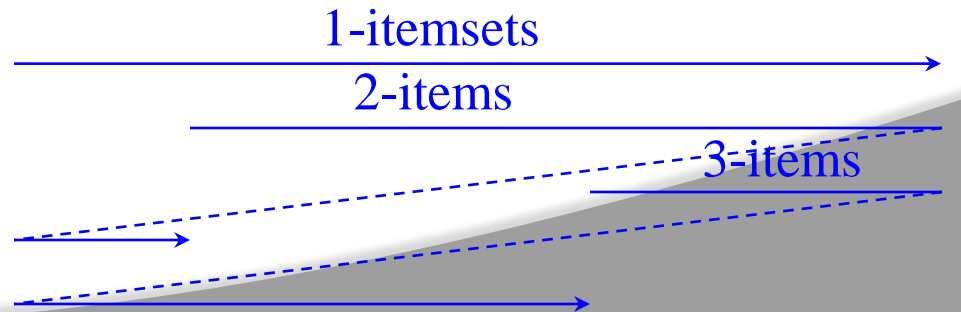
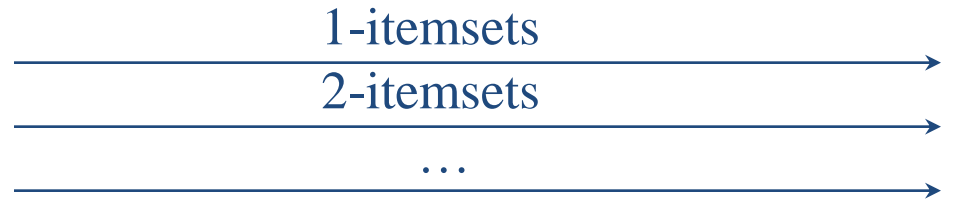
DIC: Reduce Number of Scans



Itemset lattice

S. Brin R. Motwani, J. Ullman, and S. Tsur. Dynamic itemset counting and implication rules for market basket data. In *SIGMOD'97*

- Once both A and D are determined frequent, the counting of AD begins
- Once all length-2 subsets of BCD are determined frequent, the counting of BCD begins



DIC

- Multiple database scans are **costly**
- Mining long patterns needs many passes of scanning and generates lots of candidates
 - To find frequent itemset $i_1i_2\dots i_{100}$
 - # of scans: **100**
 - # of Candidates: $\binom{100}{1} + \binom{100}{2} + \dots + \binom{100}{100} = 2^{100} - 1 =$
 1.27×10^{30} !
- Bottleneck: candidate-generation-and-test
- Can we avoid candidate generation?

- Grow long patterns from short ones using local frequent items
 - “abc” is a frequent pattern
 - Get all transactions having “abc”: DB|abc
 - “d” is a local frequent item in DB|abc → abcd is a frequent pattern

Construct FP-tree from a Transaction Database

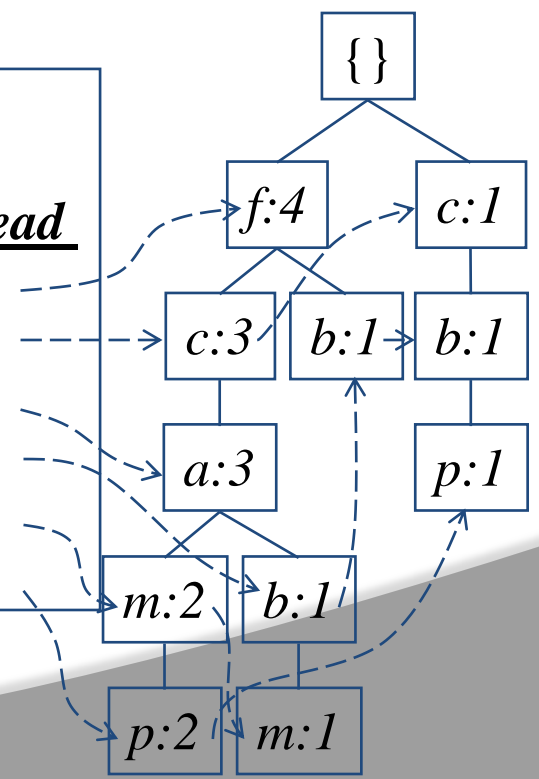
<i>TID</i>	<i>Items bought</i>	<i>(ordered) frequent items</i>
100	{f, a, c, d, g, i, m, p}	{f, c, a, m, p}
200	{a, b, c, f, l, m, o}	{f, c, a, b, m}
300	{b, f, h, j, o, w}	{f, b}
400	{b, c, k, s, p}	{c, b, p}
500	{a, f, c, e, l, p, m, n}	{f, c, a, m, p}

min_support = 3

1. Scan DB once, find frequent 1-itemset (single item pattern)
2. Sort frequent items in frequency descending order, f-list
3. Scan DB again, construct FP-tree

Header Table	
<u><i>Item frequency head</i></u>	
<i>f</i>	4
<i>c</i>	4
<i>a</i>	3
<i>b</i>	3
<i>m</i>	3
<i>p</i>	3

F-list=f-c-a-b-m-p



Benefits of the FP-tree Structure

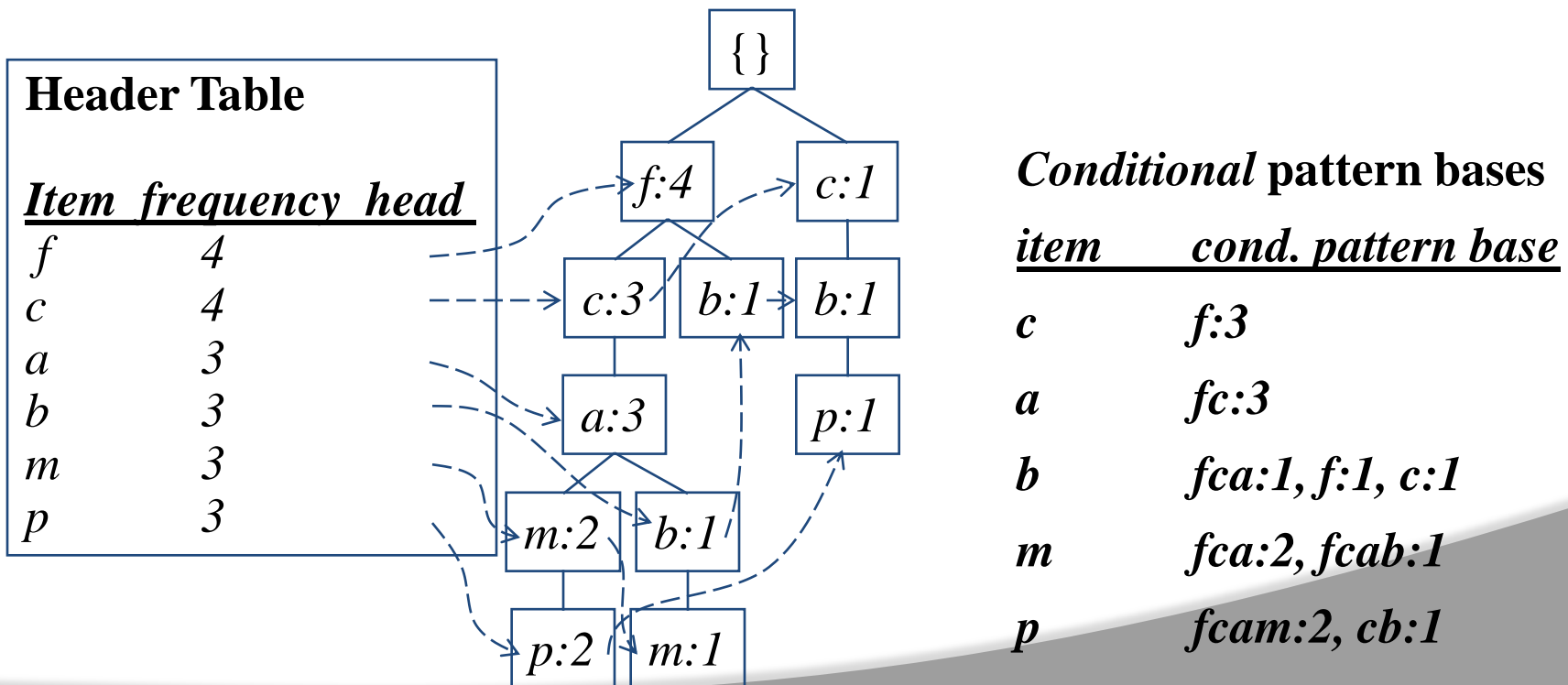
- Completeness
 - Preserve complete information for frequent pattern mining
 - Never break a long pattern of any transaction
- Compactness
 - Reduce irrelevant info—infrequent items are gone
 - Items in frequency descending order: the more frequently occurring, the more likely to be shared
 - Never be larger than the original database (not count node-links and the *count* field)
 - For Connect-4 DB, compression ratio could be over 100

Partition Patterns and Databases

- Frequent patterns can be partitioned into subsets according to f-list
 - F-list=f-c-a-b-m-p
 - Patterns containing p
 - Patterns having m but no p
 - ...
 - Patterns having c but no a nor b, m, p
 - Pattern f
- Completeness and non-redundancy

Find Patterns Having P From P-conditional Database

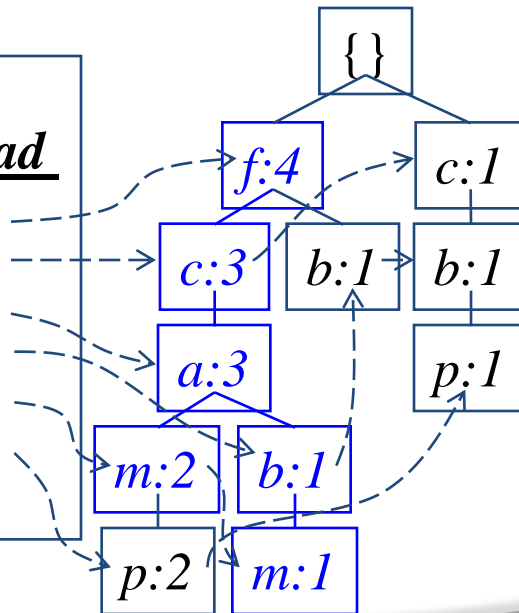
- Starting at the frequent item header table in the FP-tree
- Traverse the FP-tree by following the link of each frequent item p
- Accumulate all of *transformed prefix paths* of item p to form p 's conditional pattern base



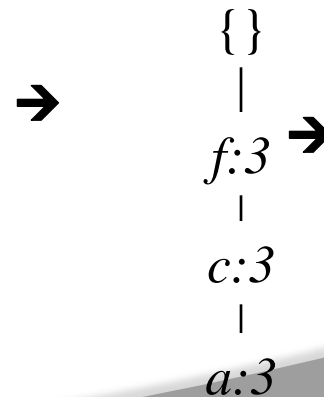
From Conditional Pattern-bases to Conditional FP-trees

- For each pattern-base
 - Accumulate the count for each item in the base
 - Construct the FP-tree for the frequent items of the pattern base

Header Table	
<u>Item frequency head</u>	
<i>f</i>	4
<i>c</i>	4
<i>a</i>	3
<i>b</i>	3
<i>m</i>	3
<i>p</i>	3



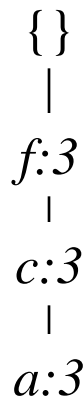
m-conditional pattern base:
fca:2, fcab:1



All frequent patterns relate to *m*
m,
fm, cm, am,
fcm, fam, cam,
fcam

m-conditional FP-tree

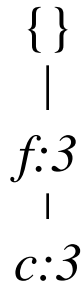
Recursion: Mining Each Conditional FP-tree



m-conditional FP-tree

Cond. pattern base of "am": (fc:3)

Cond. pattern base of "cm": (f:3)



am-conditional FP-tree



cm-conditional FP-tree

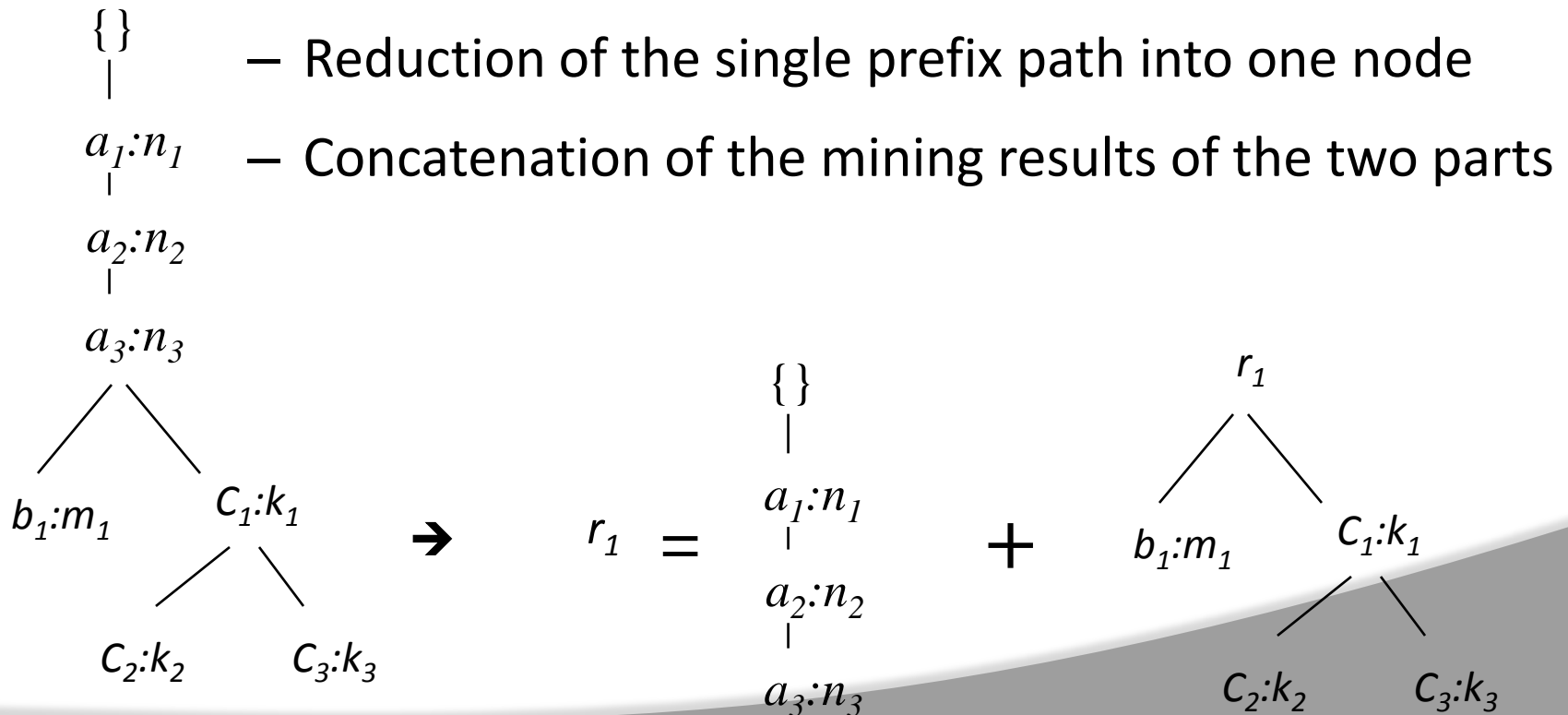
Cond. pattern base of "cam": (f:3)



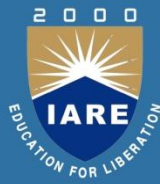
cam-conditional FP-tree

A Special Case: Single Prefix Path in FP-tree

- Suppose a (conditional) FP-tree T has a shared single prefix-path P
- Mining can be decomposed into two parts



Mining Frequent Patterns With FP-trees



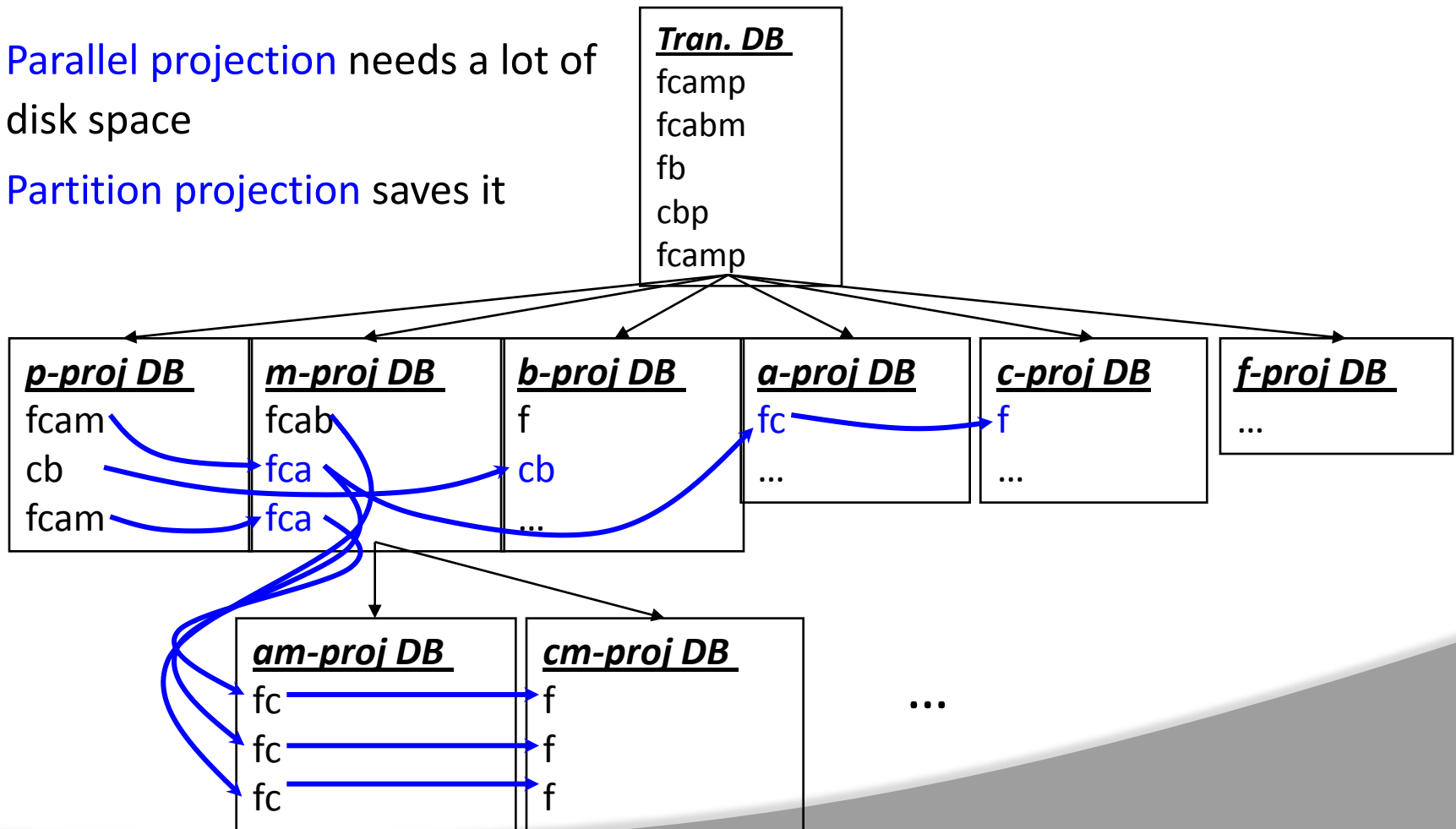
- Idea: Frequent pattern growth
 - Recursively grow frequent patterns by pattern and database partition
- Method
 - For each frequent item, construct its conditional pattern-base, and then its conditional FP-tree
 - Repeat the process on each newly created conditional FP-tree
 - Until the resulting FP-tree is empty, or it contains only one path—single path will generate all the combinations of its sub-paths, each of which is a frequent pattern

Scaling FP-growth by DB Projection

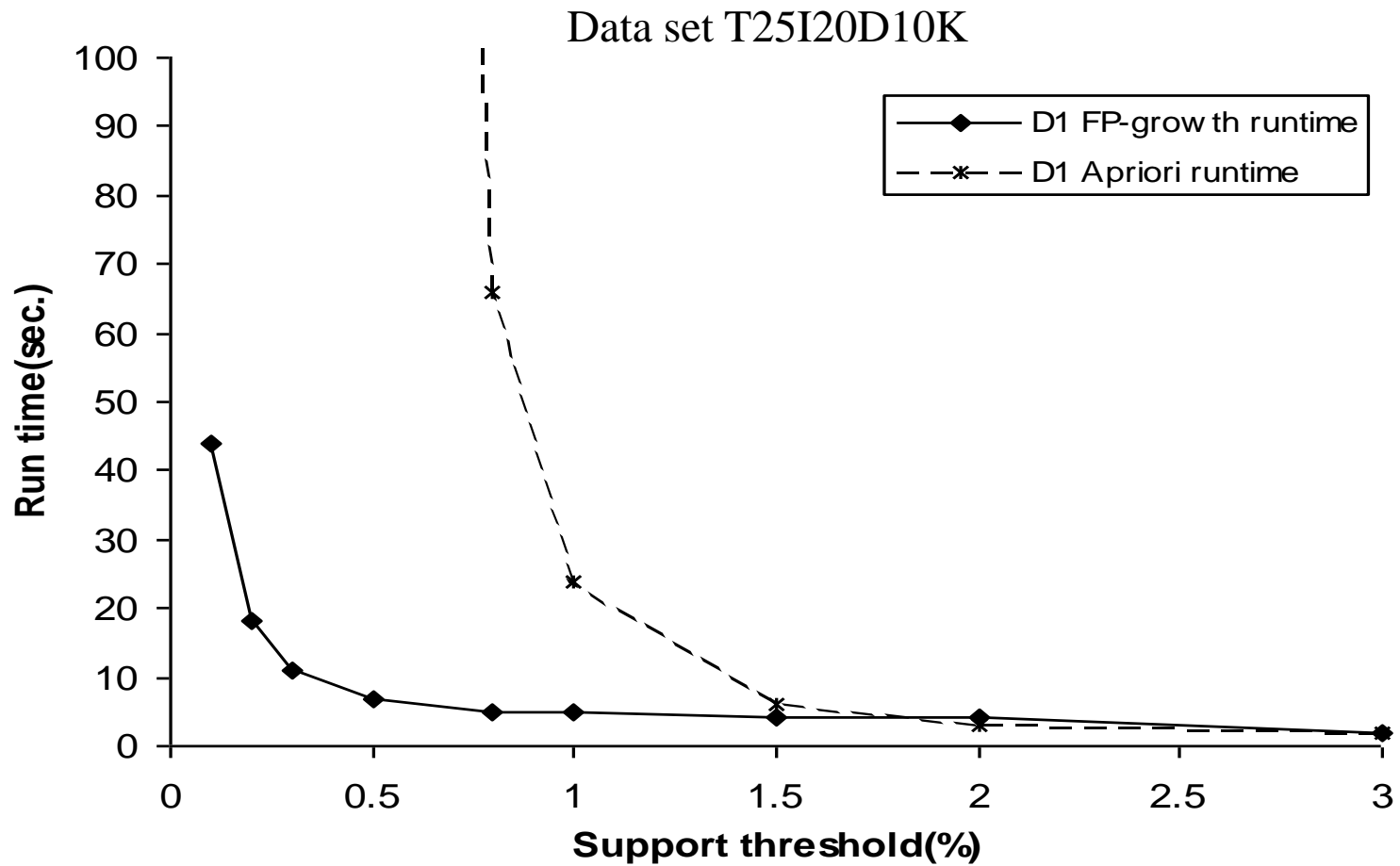
- FP-tree cannot fit in memory?—DB projection
- First partition a database into a set of projected DBs
- Then construct and mine FP-tree for each projected DB
- Parallel projection vs. Partition projection techniques
 - Parallel projection is space costly

Partition-based Projection

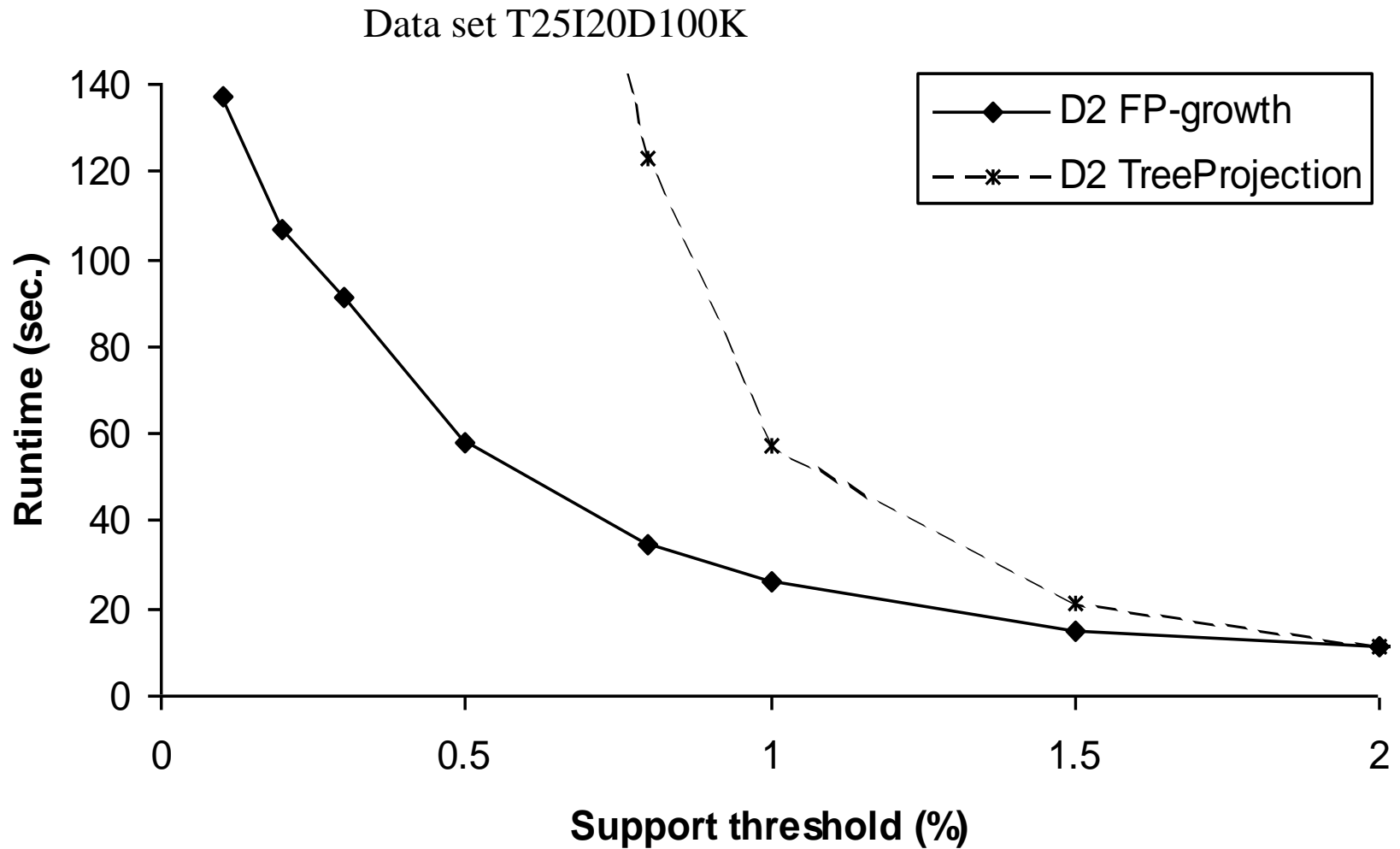
- Parallel projection needs a lot of disk space
- Partition projection saves it



FP-Growth vs. Apriori: Scalability With the Support Threshold



FP-Growth vs. Tree-Projection: Scalability with the Support Threshold



Why Is FP-Growth the Winner?

- Divide-and-conquer:
 - decompose both the mining task and DB according to the frequent patterns obtained so far
 - leads to focused search of smaller databases
- Other factors
 - no candidate generation, no candidate test
 - compressed database: FP-tree structure
 - no repeated scan of entire database
 - basic ops—counting local freq items and building sub FP-tree, no pattern search and matching

Implications of the Methodology

- Mining closed frequent itemsets and max-patterns
 - CLOSET (DMKD'00)
- Mining sequential patterns
 - FreeSpan (KDD'00), PrefixSpan (ICDE'01)
- Constraint-based mining of frequent patterns
 - Convertible constraints (KDD'00, ICDE'01)
- Computing iceberg data cubes with complex measures
 - H-tree and H-cubing algorithm (SIGMOD'01)

MaxMiner: Mining Max-patterns

- 1st scan: find frequent items
 - A, B, C, D, E
- 2nd scan: find support for
 - AB, AC, AD, AE, **ABCDE**
 - BC, BD, BE, **BCDE**
 - CD, CE, **CDE**, DE,

Tid	Items
10	A,B,C,D,E
20	B,C,D,E,
30	A,C,D,F

Potential max-patterns

- Since BCDE is a max-pattern, no need to check BCD, BDE, CDE in later scan
- R. Bayardo. **Efficiently mining long patterns from databases**. In *SIGMOD'98*

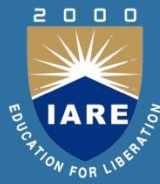
Mining Frequent Closed Patterns: CLOSET

- Flist: list of all frequent items in support ascending order
 - Flist: d-a-f-e-c
- Divide search space
 - Patterns having d
 - Patterns having d but no a, etc.
- Find frequent closed pattern recursively
 - Every transaction having d also has cfa → cfad is a frequent closed pattern
- J. Pei, J. Han & R. Mao. "CLOSET: An Efficient Algorithm for Mining Frequent Closed Itemsets", DMKD'00.

Min_sup=2

TID	Items
10	a, c, d, e, f
20	a, b, e
30	c, e, f
40	a, c, d, f
50	c, e, f

CLOSET: Mining Closed Itemsets by Pattern-Growth



- Itemset merging: if Y appears in every occurrence of X , then Y is merged with X
- Sub-itemset pruning: if $Y \supset X$, and $\text{sup}(X) = \text{sup}(Y)$, X and all of X 's descendants in the set enumeration tree can be pruned
- Hybrid tree projection
 - Bottom-up physical tree-projection
 - Top-down pseudo tree-projection
- Item skipping: if a local frequent item has the same support in several header tables at different levels, one can prune it from the header table at higher levels
- Efficient subset checking

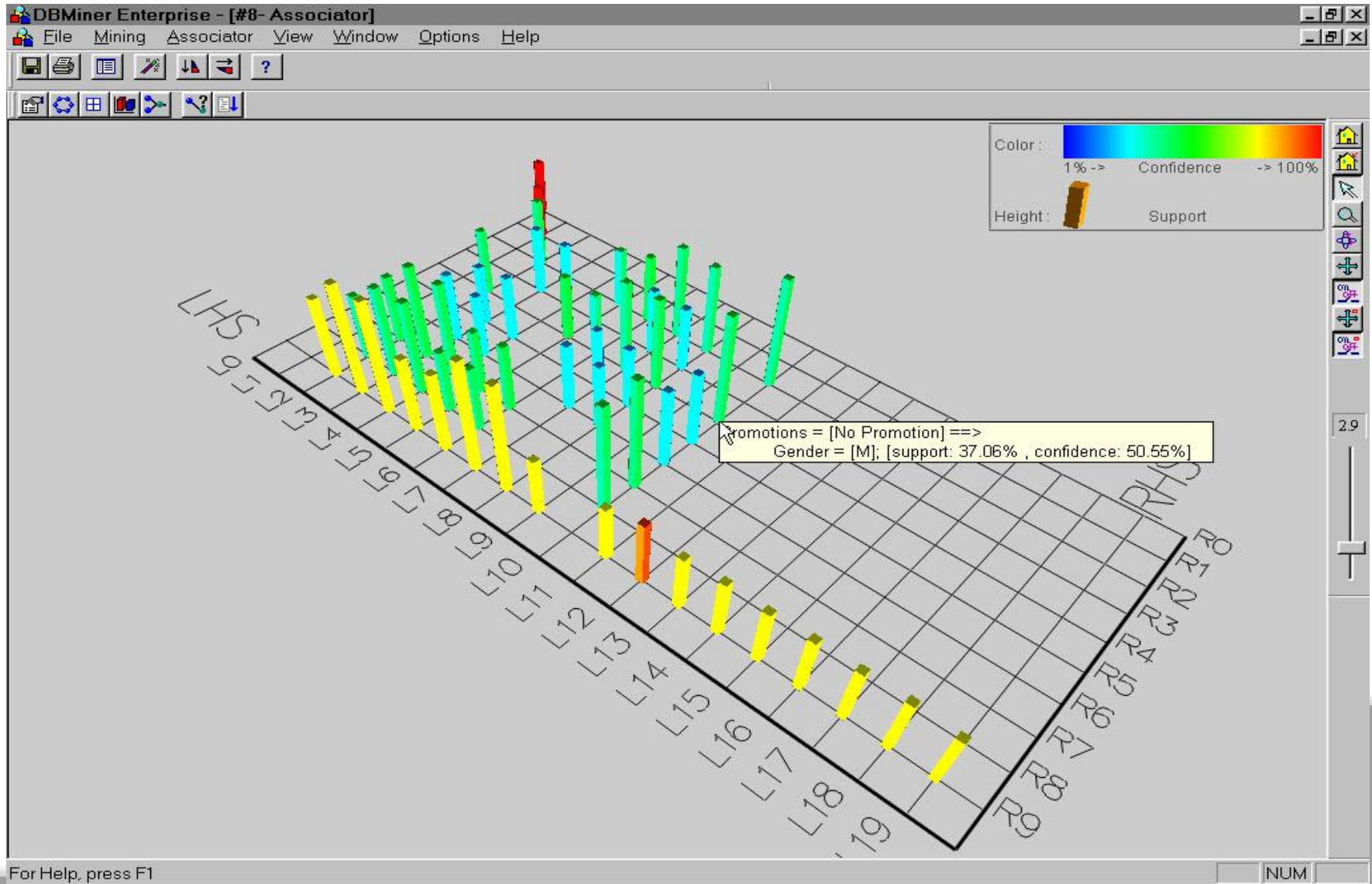
CHARM: Mining by Exploring Vertical Data Format

- Vertical format: $t(AB) = \{T_{11}, T_{25}, \dots\}$
 - tid-list: list of trans.-ids containing an itemset
- Deriving closed patterns based on vertical intersections
 - $t(X) = t(Y)$: X and Y always happen together
 - $t(X) \subset t(Y)$: transaction having X always has Y
- Using **diffset** to accelerate mining
 - Only keep track of differences of tids
 - $t(X) = \{T_1, T_2, T_3\}$, $t(XY) = \{T_1, T_3\}$
 - Diffset $(XY, X) = \{T_2\}$
- Eclat/MaxEclat (Zaki et al. @KDD'97), VIPER(P. Shenoy et al.@SIGMOD'00), CHARM (Zaki & Hsiao@SDM'02)

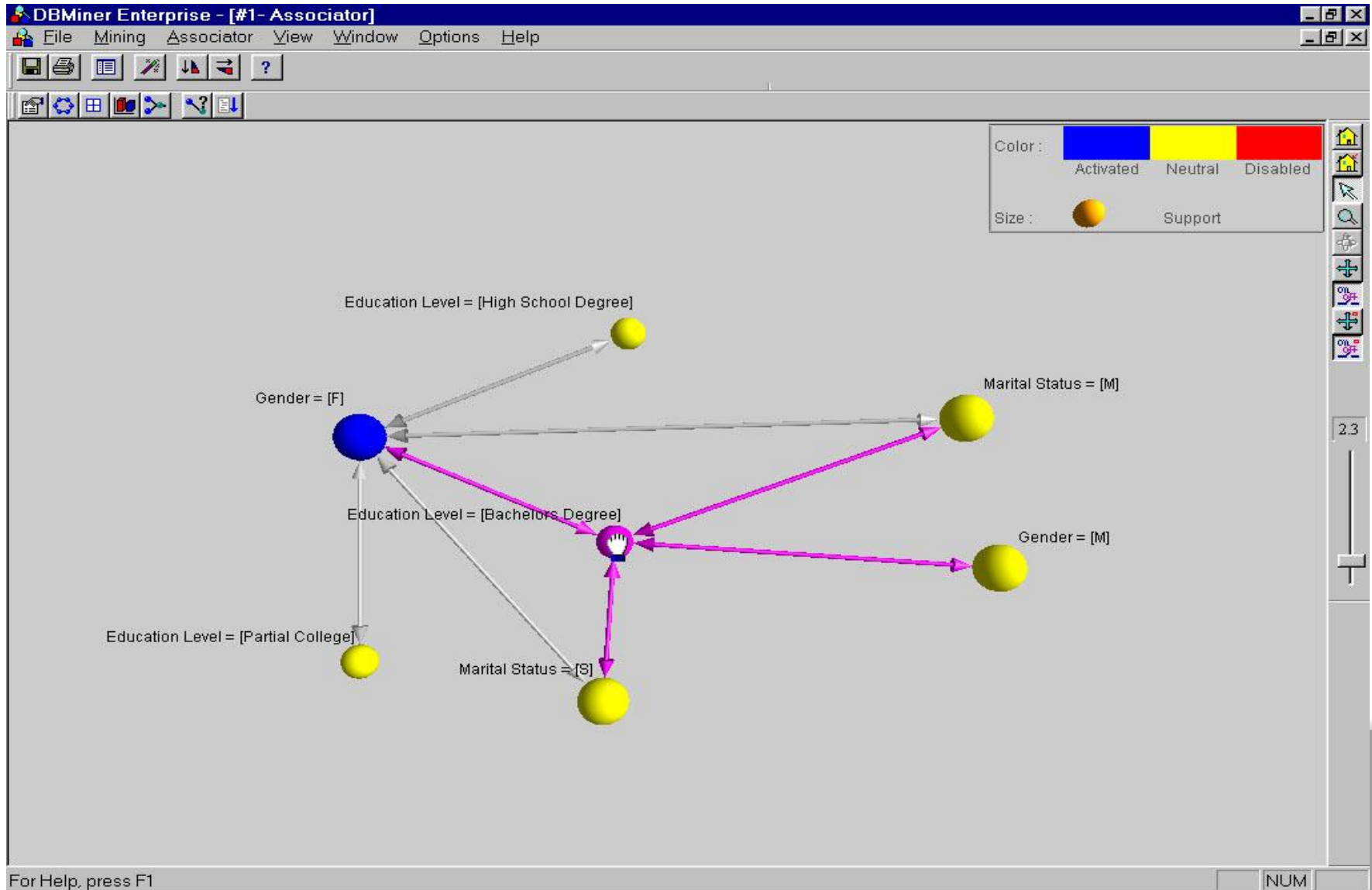
Further Improvements of Mining Methods

- AFOPT (Liu, et al. @ KDD'03)
 - A “push-right” method for mining condensed frequent pattern (CFP) tree
- Carpenter (Pan, et al. @ KDD'03)
 - Mine data sets with small rows but numerous columns
 - Construct a row-enumeration tree for efficient mining

Visualization of Association Rules: Plane Graph



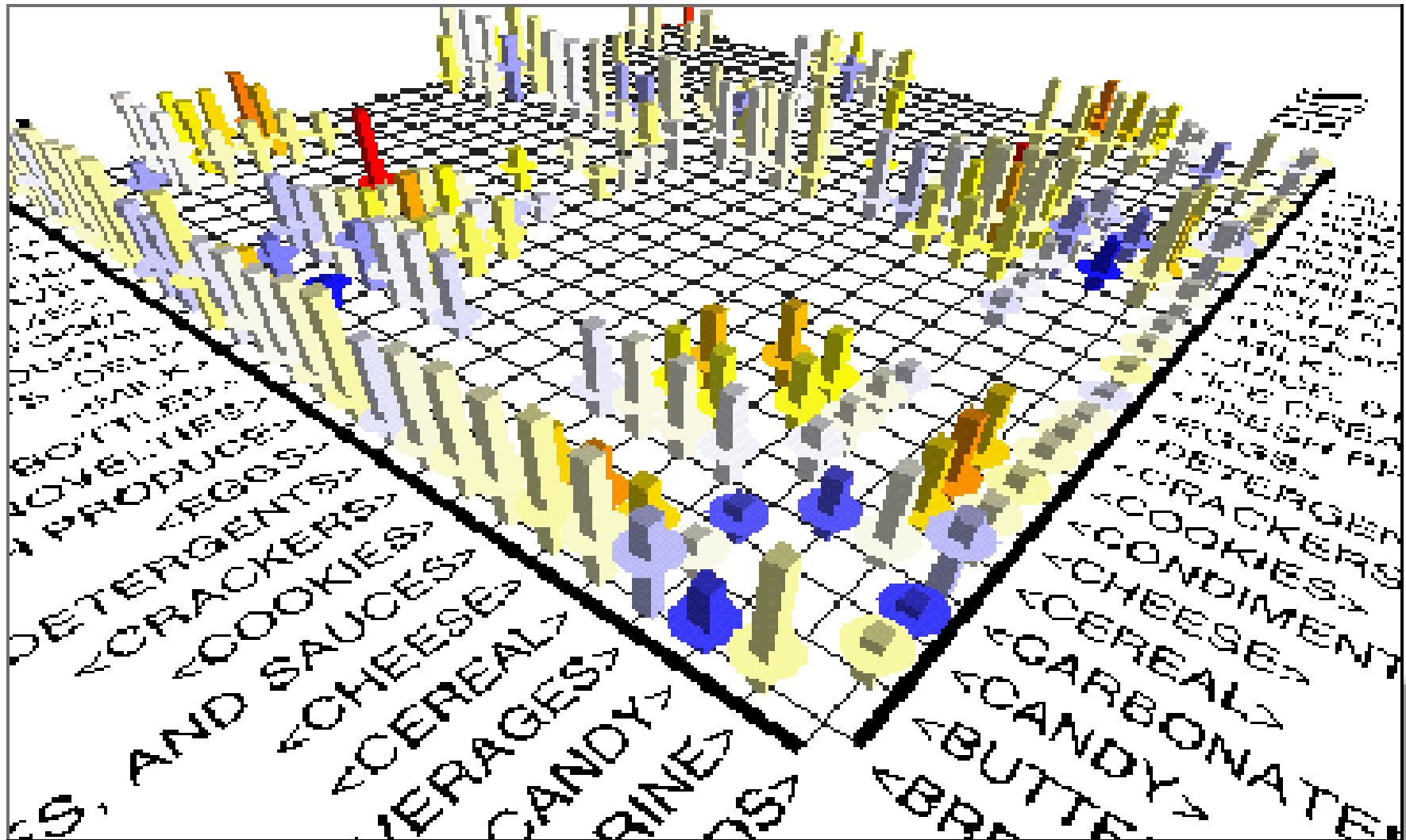
Visualization of Association Rules: Rule Graph



Frequent-Pattern Mining: Research Problems

- Mining fault-tolerant frequent, sequential and structured patterns
 - Patterns allows limited faults (insertion, deletion, mutation)
- Mining truly interesting patterns
 - Surprising, novel, concise, ...
- Application exploration
 - E.g., DNA sequence analysis and bio-pattern classification
 - “Invisible” data mining

Visualization of Association Rules (SGI/MineSet 3.0)



Frequent-Pattern Mining: Summary

- Frequent pattern mining—an important task in data mining
- Scalable frequent pattern mining methods
 - Apriori (Candidate generation & test)
 - Projection-based (FPgrowth, CLOSET+, ...)
 - Vertical format approach (CHARM, ...)
- Mining a variety of rules and interesting patterns
- Constraint-based mining
- Mining sequential and structured patterns
- Extensions and applications



MODULE– IV

CLASSIFICATION AND PRIDITION

CLOs	Course Learning Outcome
CLO13	Understand the classification problem and Bayesian classification
CLO14	Illustrate the rule based and back propagation classification algorithms
CLO15	Understand the Cluster and Analysis
CLO16	Understand the Types of data and categorization of major clustering methods

CONTENTS

- What is classification?
- What is prediction?
- Issues regarding classification and prediction
- Classification by decision tree induction
- Bayesian classification
- Lazy learners (or learning from your neighbors)

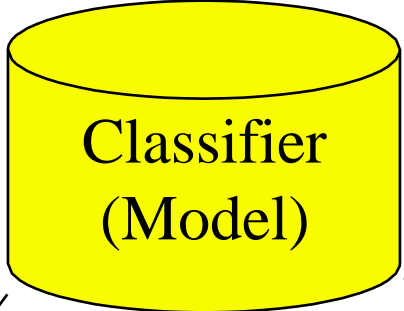
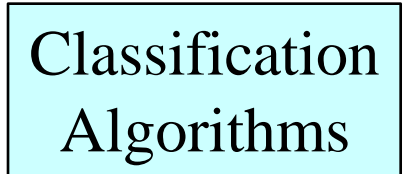
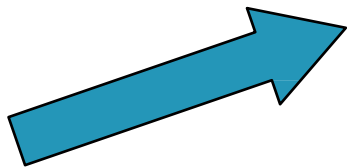
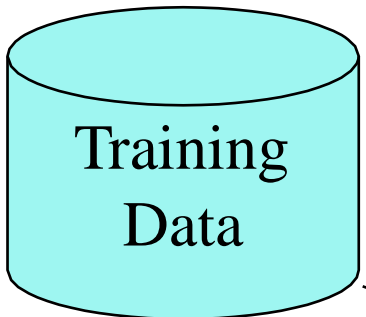
Classification vs. Prediction

- Classification
 - predicts categorical class labels (discrete or nominal)
 - classifies data (constructs a model) based on the training set and the values (class labels) in a classifying attribute and uses it in classifying new data
- Prediction
 - models continuous-valued functions, i.e., predicts unknown or missing values
- Typical applications
 - Credit approval
 - Target marketing
 - Medical diagnosis
 - Fraud detection

Classification—A Two-Step Process

- Model construction: describing a set of predetermined classes
 - Each tuple/sample is assumed to belong to a predefined class, as determined by the class label attribute
 - The set of tuples used for model construction is training set
 - The model is represented as classification rules, decision trees, or mathematical formulae
- Model usage: for classifying future or unknown objects
 - Estimate accuracy of the model
 - The known label of test sample is compared with the classified result from the model
 - Accuracy rate is the percentage of test set samples that are correctly classified by the model
 - Test set is independent of training set, otherwise over-fitting will occur
 - If the accuracy is acceptable, use the model to classify data tuples whose class labels are not known

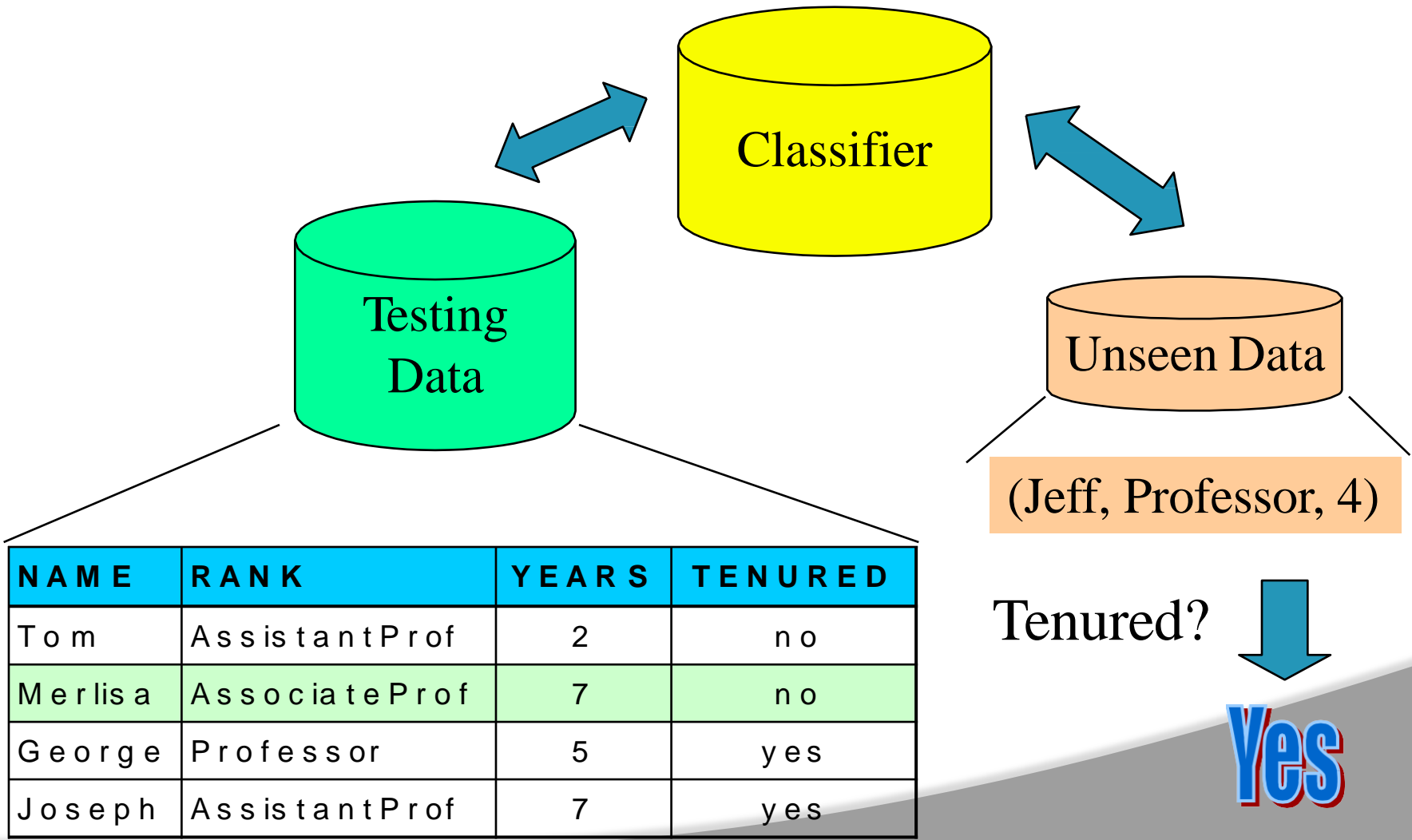
Process (1): Model Construction



NAME	RANK	YEARS	TENURED
Mike	AssistantProf	3	no
Mary	AssistantProf	7	yes
Bill	Professor	2	yes
Jim	AssociateProf	7	yes
Dave	AssistantProf	6	no
Anne	AssociateProf	3	no

IF rank = 'professor'
OR years > 6
THEN tenured = 'yes'

Process (2): Using the Model in Prediction



Supervised vs. Unsupervised Learning

- Supervised learning (classification)
 - Supervision: The training data (observations, measurements, etc.) are accompanied by labels indicating the class of the observations
 - New data is classified based on the training set
- Unsupervised learning (clustering)
 - The class labels of training data is unknown
 - Given a set of measurements, observations, etc. with the aim of establishing the existence of classes or clusters in the data

Issues: Data Preparation

- Data cleaning
 - Preprocess data in order to reduce noise and handle missing values
- Relevance analysis (feature selection)
 - Remove the irrelevant or redundant attributes
- Data transformation
 - Generalize and/or normalize data

Issues: Evaluating Classification Methods

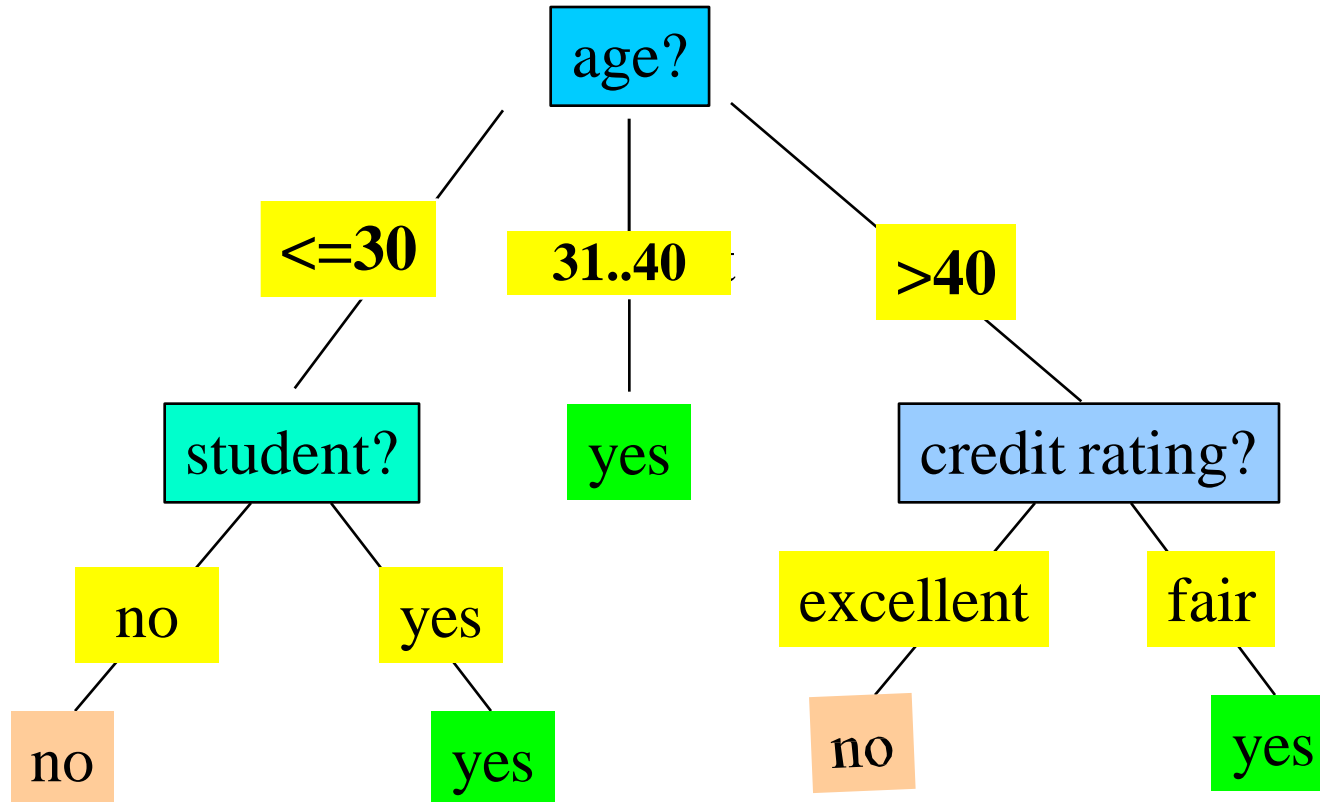
- Accuracy
 - classifier accuracy: predicting class label
 - predictor accuracy: guessing value of predicted attributes
- Speed
 - time to construct the model (training time)
 - time to use the model (classification/prediction time)
- Robustness: handling noise and missing values
- Scalability: efficiency in disk-resident databases
- Interpretability
 - understanding and insight provided by the model
- Other measures, e.g., goodness of rules, such as decision tree size or compactness of classification rules

Decision Tree Induction: Training Dataset

age	income	student	credit_rating	buys_computer
<=30	high	no	fair	no
<=30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31...40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
>40	medium	no	excellent	no

This follows an example of Quinlan's ID3 (Playing Tennis)

Output: A Decision Tree for *—buys_computer*



Algorithm for Decision Tree Induction

- Basic algorithm (a greedy algorithm)
 - Tree is constructed in a top-down recursive divide-and-conquer manner
 - At start, all the training examples are at the root
 - Attributes are categorical (if continuous-valued, they are discretized in advance)
 - Examples are partitioned recursively based on selected attributes
 - Test attributes are selected on the basis of a heuristic or statistical measure (e.g., information gain)
- Conditions for stopping partitioning
 - All samples for a given node belong to the same class
 - There are no remaining attributes for further partitioning – majority voting is employed for classifying the leaf
 - There are no samples left

Information Gain (ID3/C4.5)

- Select the attribute with the highest information gain
- Let p_i be the probability that an arbitrary tuple in D belongs to class C_i , estimated by $|C_{i,D}|/|D|$
- Expected information (entropy) needed to classify a tuple in D :

$$Info(D) = - \sum_{i=1}^m p_i \log_2(p_i)$$

- Information needed (after using A to split D into v partitions) to classify D :

$$Info_A(D) = \sum_{j=1}^v \frac{|D_j|}{|D|} \times I(D_j)$$

- Information gained by branching on attribute A

$$Gain(A) = Info(D) - Info_A(D)$$

Information Gain

- Class P: buys_computer = ~~yes~~
- Class N: buys_computer = ~~no~~

$$Info(D) = I(9,5) = -\frac{9}{14} \log_2\left(\frac{9}{14}\right) - \frac{5}{14} \log_2\left(\frac{5}{14}\right) = 0.940$$

$$Info_{age}(D) = \frac{5}{14} I(2,3) + \frac{4}{14} I(4,0) + \frac{5}{14} I(3,2) = 0.694$$

age	p_i	n_i	$I(p_i, n_i)$
≤ 30	2	3	0.971
31...40	4	0	0
> 40	3	2	0.971

$\frac{5}{14} I(2,3)$ means $\text{age} \leq 30$ has 5 out of 14 samples, with 2 yes'es and 3 no's. Hence

$$Gain(age) = Info(D) - Info_{age}(D) = 0.246$$

Similarly,

$$Gain(income) = 0.029$$

$$Gain(student) = 0.151$$

$$Gain(credit_rating) = 0.048$$

age	income	student	credit_rating	buys_computer
≤ 30	high	no	fair	no
≤ 30	high	no	excellent	no
31...40	high	no	fair	yes
> 40	medium	no	fair	yes
> 40	low	yes	fair	yes
> 40	low	yes	excellent	no
31...40	low	yes	excellent	yes
≤ 30	medium	no	fair	no
≤ 30	low	yes	fair	yes
> 40	medium	yes	fair	yes
≤ 30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
> 40	medium	no	excellent	no

- Let attribute A be a continuous-valued attribute
- Must determine the best split point for A
 - Sort the value A in increasing order
 - Typically, the midpoint between each pair of adjacent values is considered as a possible split point
 - $(a_i + a_{i+1})/2$ is the midpoint between the values of a_i and a_{i+1}
 - The point with the minimum expected information requirement for A is selected as the split-point for A
- Split:
 - D_1 is the set of tuples in D satisfying $A \leq \text{split-point}$, and D_2 is the set of tuples in D satisfying $A > \text{split-point}$

Gain Ratio for Attribute Selection (C4.5)

- Information gain measure is biased towards attributes with a large number of values
- C4.5 (a successor of ID3) uses gain ratio to overcome the problem (normalization to information gain)

$$SplitInfo_A(D) = - \sum_{j=1}^v \frac{|D_j|}{|D|} \times \log_2 \left(\frac{|D_j|}{|D|} \right)$$

- $GainRatio(A) = Gain(A)/SplitInfo(A)$

- **Ex.** $SplitInfo_A(D) = - \frac{4}{14} \times \log_2 \left(\frac{4}{14} \right) - \frac{6}{14} \times \log_2 \left(\frac{6}{14} \right) - \frac{4}{14} \times \log_2 \left(\frac{4}{14} \right) = 0.926$

- $gain_ratio(income) = 0.029/0.926 = 0.031$

- The attribute with the maximum gain ratio is selected as the splitting attribute

Gini index (CART, IBM IntelligentMiner)

- If a data set D contains examples from n classes, gini index, $\text{gini}(D)$ is defined as

$$\text{gini}(D) = 1 - \sum_{j=1}^n p_j^2$$

where p_j is the relative frequency of class j in D

- If a data set D is split on A into two subsets D_1 and D_2 , the gini index $\text{gini}_A(D)$ is defined as

$$\text{gini}_A(D) = \frac{|D_1|}{|D|} \text{gini}(D_1) + \frac{|D_2|}{|D|} \text{gini}(D_2)$$

- Reduction in Impurity:

$$\Delta \text{gini}(A) = \text{gini}(D) - \text{gini}_A(D)$$

- The attribute provides the smallest $\text{gini}_{\text{split}}(D)$ (or the largest reduction in impurity) is chosen to split the node (need to enumerate all the possible splitting points for each attribute)

Gini index (CART, IBM IntelligentMiner)

- Ex. D has 9 tuples in $\text{buys_computer} = \text{yes}$ and 5 in no

$$gini(D) = 1 - \left| \left(\frac{9}{14} \right)^2 - \left(\frac{5}{14} \right)^2 \right| = 0.459$$

- Suppose the attribute income partitions D into 10 in D_1 : {low, medium} and 4 in D_2

$$\begin{aligned}
 gini_{income \in \{low, medium\}}(D) &= \left(\frac{10}{14} \right) Gini(D) + \left(\frac{4}{14} \right) Gini(D) \\
 &= \frac{10}{14} \left(1 - \left(\frac{6}{10} \right)^2 - \left(\frac{4}{10} \right)^2 \right) + \frac{4}{14} \left(1 - \left(\frac{1}{4} \right)^2 - \left(\frac{3}{4} \right)^2 \right) \\
 &= 0.450 \\
 &= Gini_{income \in \{high\}}(D)
 \end{aligned}$$

but $gini_{\{medium, high\}}$ is 0.30 and thus the best since it is the lowest

- All attributes are assumed continuous-valued
- May need other tools, e.g., clustering, to get the possible split values
- Can be modified for categorical attributes

Comparing Attribute Selection Measures

- The three measures, in general, return good results but
 - Information gain:
 - biased towards multivalued attributes
 - Gain ratio:
 - tends to prefer unbalanced splits in which one partition is much smaller than the others
 - Gini index:
 - biased to multivalued attributes
 - has difficulty when # of classes is large
 - tends to favor tests that result in equal-sized partitions and purity in both partitions

Other Attribute Selection Measures

- CHAID: a popular decision tree algorithm, measure based on χ^2 test for independence
- C-SEP: performs better than info. gain and gini index in certain cases
- G-statistics: has a close approximation to χ^2 distribution
- MDL (Minimal Description Length) principle (i.e., the simplest solution is preferred):
 - The best tree as the one that requires the fewest # of bits to both (1) encode the tree, and (2) encode the exceptions to the tree
- Multivariate splits (partition based on multiple variable combinations)
 - CART: finds multivariate splits based on a linear comb. of attrs.
- Which attribute selection measure is the best?
 - Most give good results, none is significantly superior than others

Overfitting and Tree Pruning

- **Overfitting:** An induced tree may overfit the training data
 - Too many branches, some may reflect anomalies due to noise or outliers
 - Poor accuracy for unseen samples
- **Two approaches to avoid overfitting**
 - **Prepruning:** Halt tree construction early—do not split a node if this would result in the goodness measure falling below a threshold
 - Difficult to choose an appropriate threshold
 - **Postpruning:** Remove branches from a —fullygrown tree—get a sequence of progressively pruned trees
 - Use a set of data different from the training data to decide which is the —bestpruned tree

Enhancements to Basic Decision Tree Induction

- Allow for continuous-valued attributes
 - Dynamically define new discrete-valued attributes that partition the continuous attribute value into a discrete set of intervals
- Handle missing attribute values
 - Assign the most common value of the attribute
 - Assign probability to each of the possible values
- Attribute construction
 - Create new attributes based on existing ones that are sparsely represented
 - This reduces fragmentation, repetition, and replication

Classification in Large Databases

- Classification—a classical problem extensively studied by statisticians and machine learning researchers
- Scalability: Classifying data sets with millions of examples and hundreds of attributes with reasonable speed
- Why decision tree induction in data mining?
 - relatively faster learning speed (than other classification methods)
 - convertible to simple and easy to understand classification rules
 - can use SQL queries for accessing databases
 - comparable classification accuracy with other methods

Scalable Decision Tree Induction Methods

- SLIQ (EDBT'96 — Mehta et al.)
 - Builds an index for each attribute and only class list and the current attribute list reside in memory
- SPRINT (VLDB'96 — J. Shafer et al.)
 - Constructs an attribute list data structure
- PUBLIC (VLDB'98 — Rastogi & Shim)
 - Integrates tree splitting and tree pruning: stop growing the tree earlier
- RainForest (VLDB'98 — Gehrke, Ramakrishnan & Ganti)
 - Builds an AVC-list (attribute, value, class label)
- BOAT (PODS'99 — Gehrke, Ganti, Ramakrishnan & Loh)
 - Uses bootstrapping to create several small samples

Scalability Framework for RainForest

- Separates the scalability aspects from the criteria that determine the quality of the tree
- Builds an AVC-list: AVC (Attribute, Value, Class_label)
- AVC-set (of an attribute X)
 - Projection of training dataset onto the attribute X and class label where counts of individual class label are aggregated
- AVC-group (of a node n)
 - Set of AVC-sets of all predictor attributes at the node n

Rainforest: Training Set and Its AVC Sets

Training Examples

age	income	student	redit_ratin	_co m
<=30	high	no	fair	no
<=30	high	no	excellent	no
31..40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31..40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31..40	medium	no	excellent	yes
31..40	high	yes	fair	yes
>40	medium	no	excellent	no

AVC-set on *Age*

Age	Buy_Computer	
	yes	no
<=30	3	2
31..40	4	0
>40	3	2

AVC-set on *income*

income	Buy_Computer	
	yes	no
high	2	2
medium	4	2
low	3	1

AVC-set on *Student*

student	Buy_Computer	
	yes	no
yes	6	1
no	3	4

AVC-set on *credit_rating*

Credit rating	Buy_Computer	
	yes	no
fair	6	2
excellent	3	3

Data Cube-Based Decision-Tree Induction

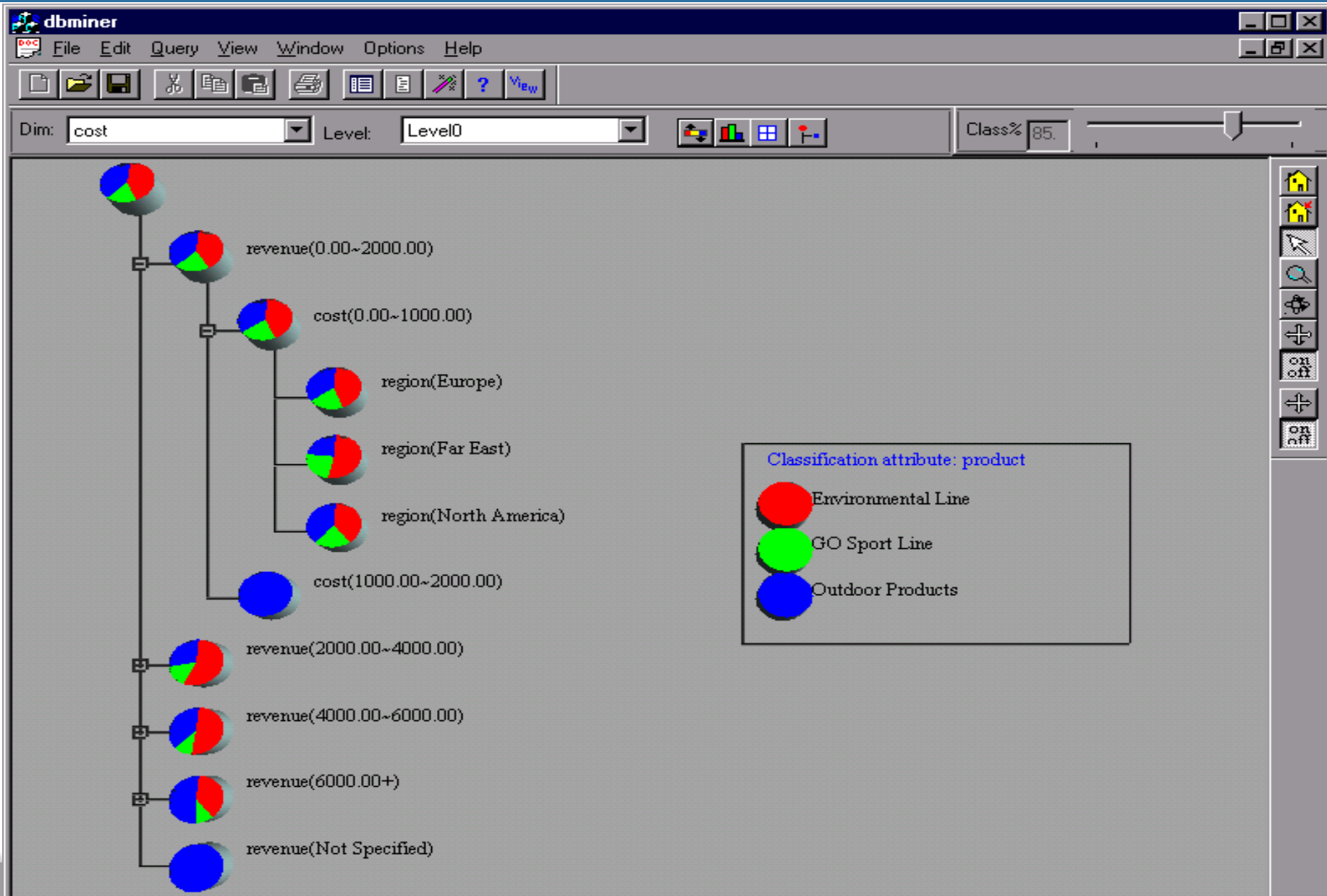
- Integration of generalization with decision-tree induction (Kamber et al.'97)
- Classification at primitive concept levels
 - E.g., precise temperature, humidity, outlook, etc.
 - Low-level concepts, scattered classes, bushy classification-trees
 - Semantic interpretation problems
- Cube-based multi-level classification
 - Relevance analysis at multi-levels
 - Information-gain analysis with dimension + level

BOAT (Bootstrapped Optimistic Algorithm for Tree Construction)

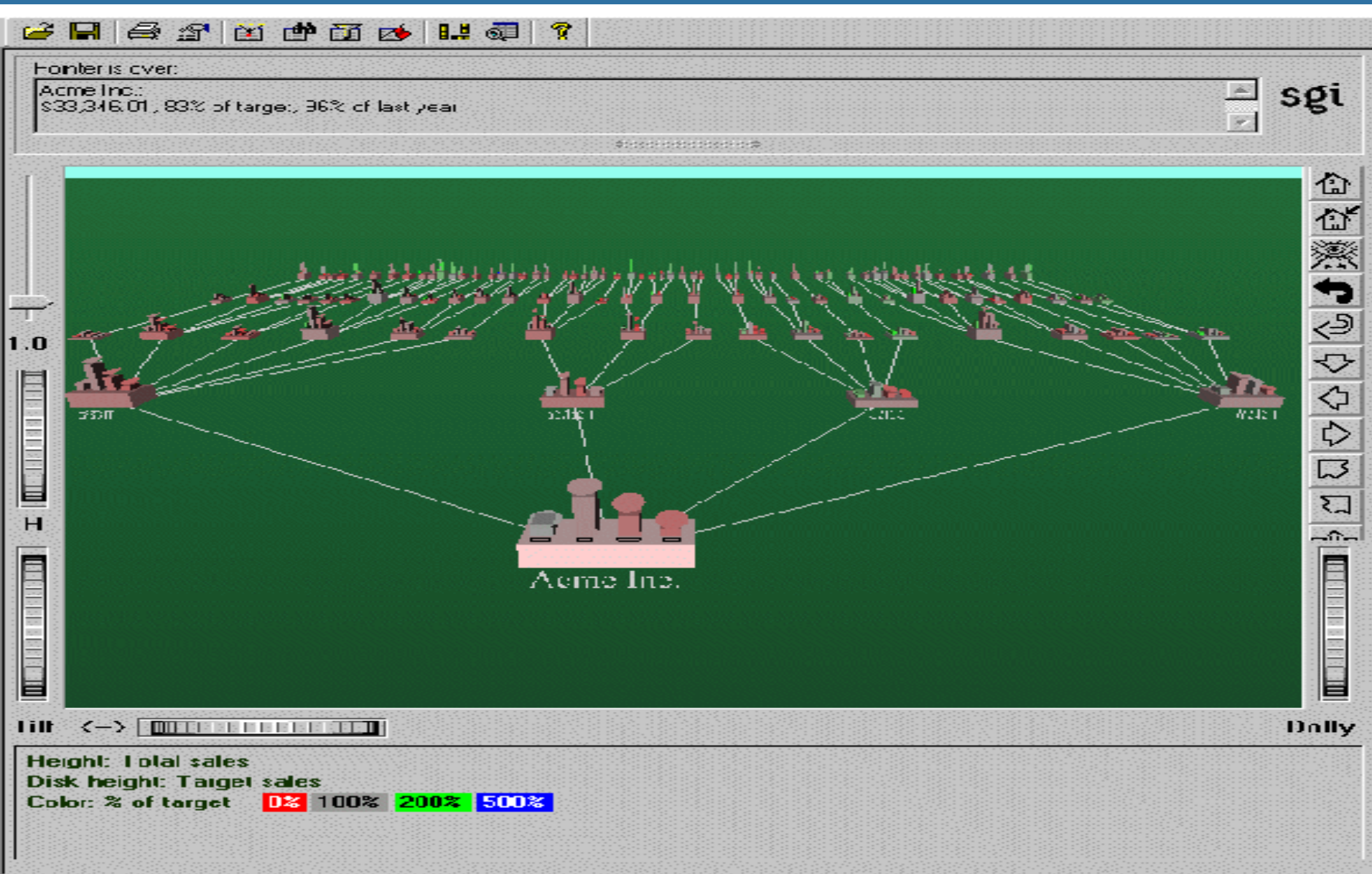


- Use a statistical technique called *bootstrapping* to create several smaller samples (subsets), each fits in memory
- Each subset is used to create a tree, resulting in several trees
- These trees are examined and used to construct a new tree T'
 - It turns out that T' is very close to the tree that would be generated using the whole data set together
- Adv: requires only two scans of DB, an incremental alg.

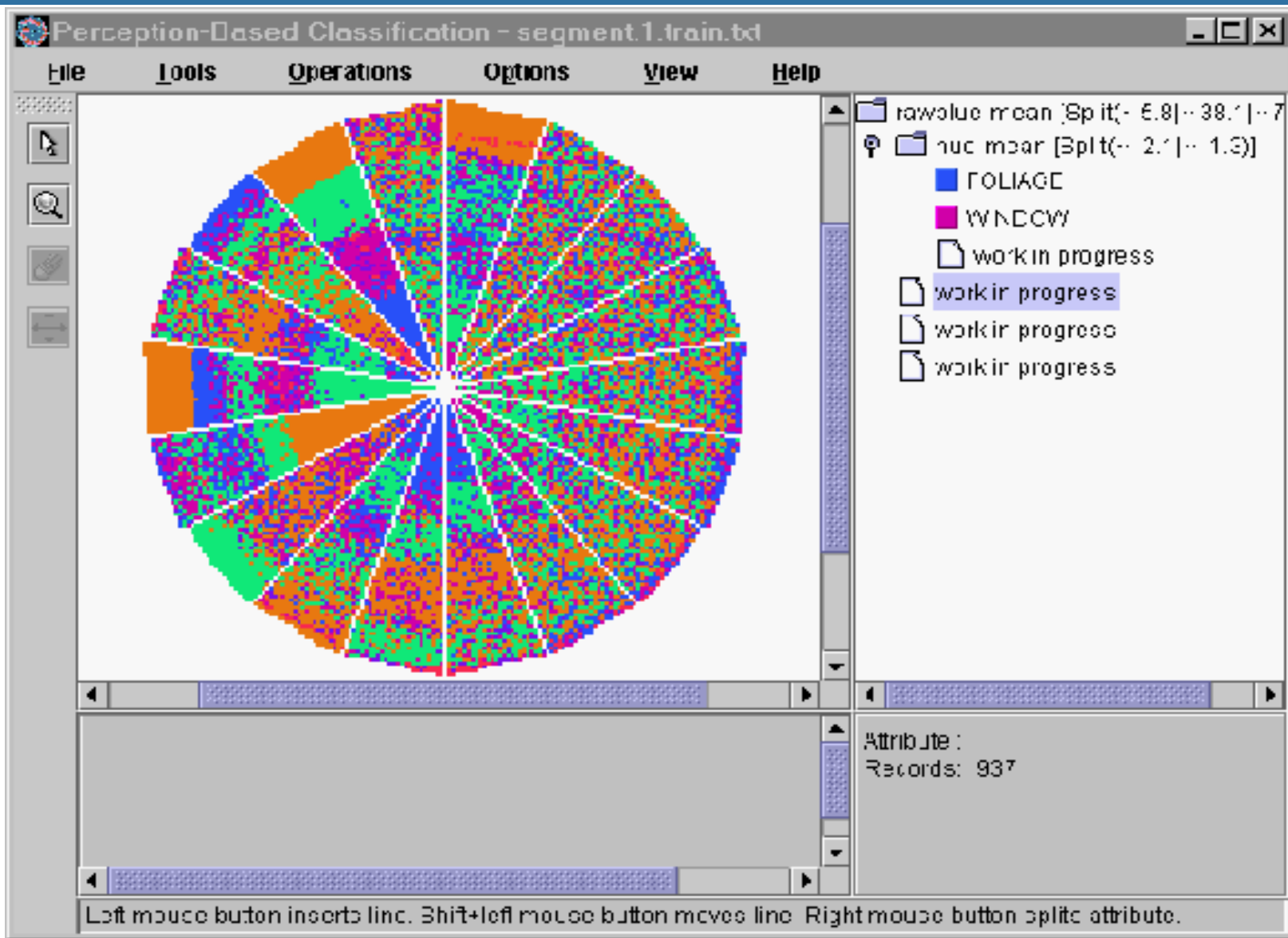
Presentation of Classification Results



Visualization of a Decision Tree in SGI/MineSet 3.0



Perception-Based Classification (PBC)



Bayesian Classification: Why?

- A statistical classifier: performs probabilistic prediction, i.e., predicts class membership probabilities
- Foundation: Based on Bayes' Theorem.
- Performance: A simple Bayesian classifier, naïve Bayesian classifier, has comparable performance with decision tree and selected neural network classifiers
- Incremental: Each training example can incrementally increase/decrease the probability that a hypothesis is correct — prior knowledge can be combined with observed data
- Standard: Even when Bayesian methods are computationally intractable, they can provide a standard of optimal decision making against which other methods can be measured

Bayesian Theorem: Basics

- Let \mathbf{X} be a data sample (*evidence*): class label is unknown
- Let H be a *hypothesis* that X belongs to class C
- Classification is to determine $P(H|\mathbf{X})$, the probability that the hypothesis holds given the observed data sample \mathbf{X}
- $P(H)$ (*prior probability*), the initial probability
 - E.g., \mathbf{X} will buy computer, regardless of age, income, ...
- $P(\mathbf{X})$: probability that sample data is observed
- $P(\mathbf{X}|H)$ (*posteriori probability*), the probability of observing the sample \mathbf{X} , given that the hypothesis holds
 - E.g., Given that \mathbf{X} will buy computer, the prob. that X is 31..40, medium income

Bayesian Theorem

- Given training data \mathbf{X} , *posteriori probability of a hypothesis* H , $P(H|\mathbf{X})$, follows the Bayes theorem

$$P(H | \mathbf{X}) = \frac{P(\mathbf{X} | H) P(H)}{P(\mathbf{X})}$$

- Informally, this can be written as
 posteriori = likelihood x prior/evidence
- Predicts \mathbf{X} belongs to C_2 iff the probability $P(C_i|\mathbf{X})$ is the highest among all the $P(C_k|X)$ for all the k classes
- Practical difficulty: require initial knowledge of many probabilities, significant computational cost

Towards Naïve Bayesian Classifier

- Let D be a training set of tuples and their associated class labels, and each tuple is represented by an n -D attribute vector $\mathbf{X} = (x_1, x_2, \dots, x_n)$
- Suppose there are m classes C_1, C_2, \dots, C_m .
- Classification is to derive the maximum posteriori, i.e., the maximal $P(C_i | \mathbf{X})$
- This can be derived from Bayes' theorem

$$P(C_i | \mathbf{X}) = \frac{P(\mathbf{X} | C_i)P(C_i)}{P(\mathbf{X})}$$

- Since $P(\mathbf{X})$ is constant for all classes, only

$$P(C_i | \mathbf{X}) \propto P(\mathbf{X} | C_i)P(C_i)$$

needs to be maximized

Derivation of Naïve Bayes Classifier

- A simplified assumption: attributes are conditionally independent (i.e., no dependence relation between attributes):

$$P(\mathbf{X} | C_i) = \prod_{k=1}^n P(x_k | C_i) = P(x_1 | C_i) \times P(x_2 | C_i) \times \dots \times P(x_n | C_i)$$

- This greatly reduces the computation cost: Only counts the class distribution
- If A_k is categorical, $P(x_k | C_i)$ is the # of tuples in C_i having value x_k for A_k divided by $|C_{i,D}|$ (# of tuples of C_i in D)
- If A_k is continuous-valued, $P(x_k | C_i)$ is usually computed based on Gaussian distribution with a mean μ and standard deviation σ

$$g(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

and $P(x_k | C_i)$ is

$$P(\mathbf{X} | C_i) = g(x_k, \mu_{C_i}, \sigma_{C_i})$$

Naïve Bayesian Classifier

Class:

C1:buys_computer = yes

C2:buys_computer = no

Data sample

X = (age <=30,

Income = medium,

Student = yes

Credit_rating = Fair)

age	income	student	redit_rating_com	
<=30	high	no	fair	no
<=30	high	no	excellent	no
31...40	high	no	fair	yes
>40	medium	no	fair	yes
>40	low	yes	fair	yes
>40	low	yes	excellent	no
31...40	low	yes	excellent	yes
<=30	medium	no	fair	no
<=30	low	yes	fair	yes
>40	medium	yes	fair	yes
<=30	medium	yes	excellent	yes
31...40	medium	no	excellent	yes
31...40	high	yes	fair	yes
>40	medium	no	excellent	no

Naïve Bayesian Classifier: An Example

- $P(C_i)$:
 - $P(\text{buys_computer} = \text{yes}) = 9/14 = 0.643$
 - $P(\text{buys_computer} = \text{no}) = 5/14 = 0.357$

- Compute $P(X|C_i)$ for each class

$$P(\text{age} = \leq 30 | \text{buys_computer} = \text{yes}) = 2/9 = 0.222$$

$$P(\text{age} = \leq 30 | \text{buys_computer} = \text{no}) = 3/5 = 0.6$$

$$P(\text{income} = \text{medium} | \text{buys_computer} = \text{yes}) = 4/9 = 0.444$$

$$P(\text{income} = \text{medium} | \text{buys_computer} = \text{no}) = 2/5 = 0.4$$

$$P(\text{student} = \text{yes} | \text{buys_computer} = \text{yes}) = 6/9 = 0.667$$

$$P(\text{student} = \text{yes} | \text{buys_computer} = \text{no}) = 1/5 = 0.2$$

$$P(\text{credit_rating} = \text{fair} | \text{buys_computer} = \text{yes}) = 6/9 = 0.667$$

$$P(\text{credit_rating} = \text{fair} | \text{buys_computer} = \text{no}) = 2/5 = 0.4$$

- $X = (\text{age} \leq 30, \text{income} = \text{medium}, \text{student} = \text{yes}, \text{credit_rating} = \text{fair})$**

$$P(X|C_i) : P(X|\text{buys_computer} = \text{yes}) = 0.222 \times 0.444 \times 0.667 \times 0.667 = 0.044$$

$$P(X|\text{buys_computer} = \text{no}) = 0.6 \times 0.4 \times 0.2 \times 0.4 = 0.019$$

$$P(X|C_i) * P(C_i) : P(X|\text{buys_computer} = \text{yes}) * P(\text{buys_computer} = \text{yes}) = 0.028$$

$$P(X|\text{buys_computer} = \text{no}) * P(\text{buys_computer} = \text{no}) = 0.007$$

Therefore, X belongs to class ("buys_computer = yes")

Avoiding the 0-Probability Problem

- Naïve Bayesian prediction requires each conditional prob. be non-zero. Otherwise, the predicted prob. will be zero

$$P(X | C_i) = \prod_{k=1}^n P(x_k | C_i)$$

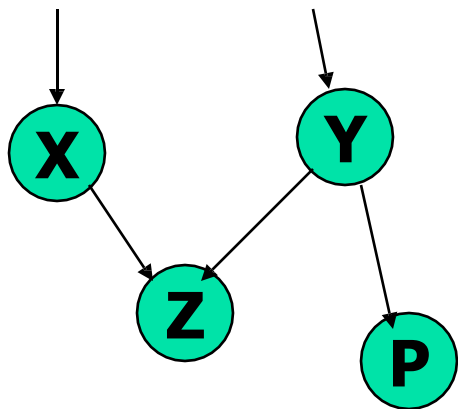
- Ex. Suppose a dataset with 1000 tuples, income=low (0), income=medium (990), and income = high (10),
- Use Laplacian correction (or Laplacian estimator)
 - Adding 1 to each case
 - Prob(income = low) = 1/1003
 - Prob(income = medium) = 991/1003
 - Prob(income = high) = 11/1003
 - The ~~corrected~~ prob. estimates are close to their ~~uncorrected~~ counterparts

Naïve Bayesian Classifier: Comments

- Advantages
 - Easy to implement
 - Good results obtained in most of the cases
- Disadvantages
 - Assumption: class conditional independence, therefore loss of accuracy
 - Practically, dependencies exist among variables
 - E.g., hospitals: patients: Profile: age, family history, etc.
Symptoms: fever, cough etc., Disease: lung cancer, diabetes, etc.
 - Dependencies among these cannot be modeled by Naïve Bayesian Classifier
- How to deal with these dependencies?
 - Bayesian Belief Networks

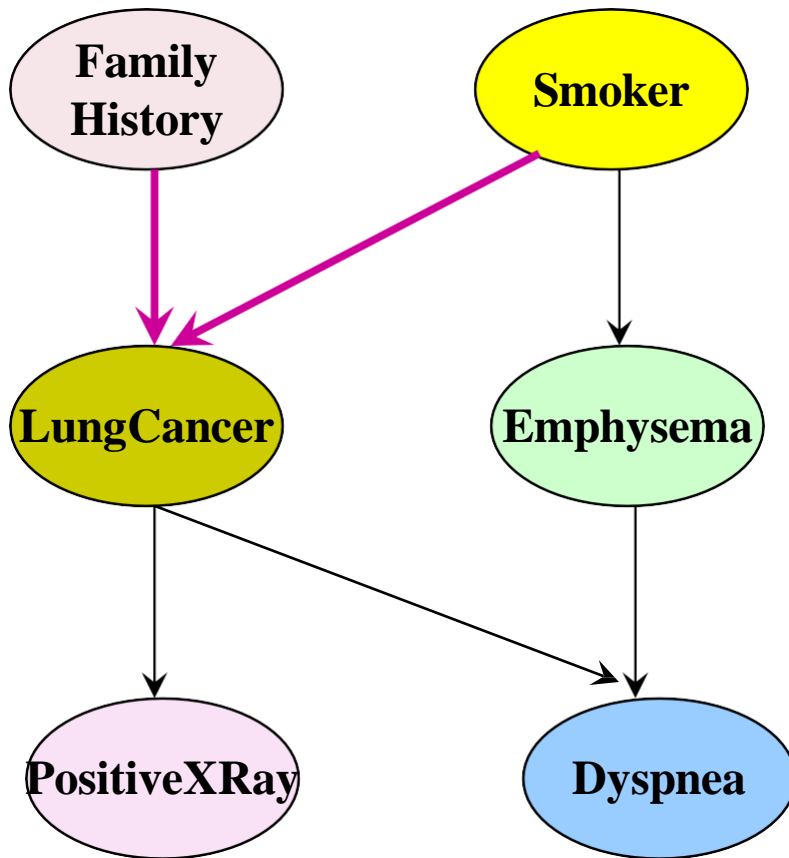
Bayesian Belief Networks

- Bayesian belief network allows a *subset* of the variables conditionally independent
- A graphical model of causal relationships
 - Represents dependency among the variables
 - Gives a specification of joint probability distribution



- Nodes: random variables
- Links: dependency
- X and Y are the parents of Z, and Y is the parent of P
- No dependency between Z and P
- Has no loops or cycles

Bayesian Belief Network: An Example



The **conditional probability table (CPT)** for variable LungCancer:

	(FH, S)	(FH, ~S)	(~FH, S)	(~FH, ~S)
LC	0.8	0.5	0.7	0.1
~LC	0.2	0.5	0.3	0.9

CPT shows the conditional probability for each possible combination of its parents

Derivation of the probability of a particular combination of values of **X**, from CPT:

Bayesian Belief Networks

$$P(x_1, \dots, x_n) = \prod_{i=1}^n P(x_i | Parents(Y_i))$$

Training Bayesian Networks

- Several scenarios:
 - Given both the network structure and all variables observable: learn only the CPTs
 - Network structure known, some hidden variables: gradient descent (greedy hill-climbing) method, analogous to neural network learning
 - Network structure unknown, all variables observable: search through the model space to reconstruct network topology
 - Unknown structure, all hidden variables: No good algorithms known for this purpose
- Ref. D. Heckerman: Bayesian networks for data mining

Lazy vs. Eager Learning

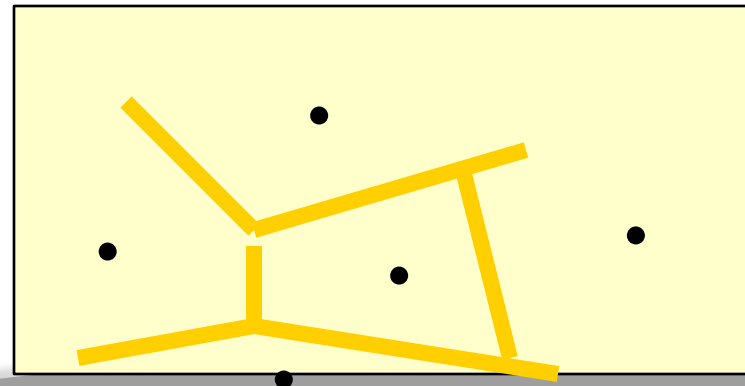
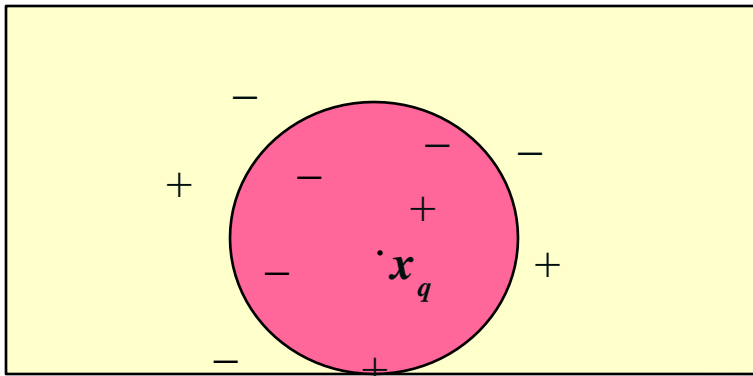
- Lazy vs. eager learning
 - Lazy learning (e.g., instance-based learning): Simply stores training data (or only minor processing) and waits until it is given a test tuple
 - Eager learning (the above discussed methods): Given a set of training set, constructs a classification model before receiving new (e.g., test) data to classify
- Lazy: less time in training but more time in predicting
- Accuracy
 - Lazy method effectively uses a richer hypothesis space since it uses many local linear functions to form its implicit global approximation to the target function
 - Eager: must commit to a single hypothesis that covers the entire instance space

Instance-Based Methods

- Instance-based learning:
 - Store training examples and delay the processing (—lazyevaluation) until a new instance must be classified
- Typical approaches
 - k-nearest neighbor approach
 - Instances represented as points in a Euclidean space.
 - Locally weighted regression
 - Constructs local approximation
 - Case-based reasoning
 - Uses symbolic representations and knowledge-based inference

The k-Nearest Neighbor Algorithm

- All instances correspond to points in the n-D space
- The nearest neighbor are defined in terms of Euclidean distance, $\text{dist}(\mathbf{X}_1, \mathbf{X}_2)$
- Target function could be discrete- or real- valued
- For discrete-valued, k -NN returns the most common value among the k training examples nearest to x_q
- Voronoi diagram: the decision surface induced by 1- NN for a typical set of training examples



Discussion on the k -NN Algorithm

- k -NN for real-valued prediction for a given unknown tuple
 - Returns the mean values of the k nearest neighbors
- Distance-weighted nearest neighbor algorithm
 - Weight the contribution of each of the k neighbors according to their distance to the query x_q
 - Give greater weight to closer neighbors
- Robust to noisy data by averaging k -nearest neighbors
- Curse of dimensionality: distance between neighbors could be dominated by irrelevant attributes
 - To overcome it, axes stretch or elimination of the least relevant attributes

$$w \equiv \frac{1}{d(x_q, x_i)^2}$$

Case-Based Reasoning (CBR)

- CBR: Uses a database of problem solutions to solve new problems
- Store symbolic description (tuples or cases)—not points in a Euclidean space
- Applications: Customer-service (product-related diagnosis), legal ruling
- Methodology
 - Instances represented by rich symbolic descriptions (e.g., function graphs)
 - Search for similar cases, multiple retrieved cases may be combined
 - Tight coupling between case retrieval, knowledge-based reasoning, and problem solving
- Challenges
 - Find a good similarity metric
 - Indexing based on syntactic similarity measure, and when failure, backtracking, and adapting to additional cases

Problems and Challenges

- Considerable progress has been made in scalable clustering methods
 - Partitioning: k-means, k-medoids, CLARANS
 - Hierarchical: BIRCH, ROCK, CHAMELEON
- Current clustering techniques do not address all the requirements adequately, still an active area of research



MODULE- V

CLUSTERING

CLOs	Course Learning Outcome
CLO17	Explore on partition algorithms for clustering.
CLO18	Explore on different hierarchical based methods, different density based methods, grid based and Model based methods.
CLO19	Understand the outlier Analysis.
CLO20	Understand mining complex data types.

What is Cluster Analysis?

- Cluster: a collection of data objects
 - Similar to one another within the same cluster
 - Dissimilar to the objects in other clusters
- Cluster analysis
 - Grouping a set of data objects into clusters
- Clustering is unsupervised classification: no predefined classes
- Typical applications
 - As a stand-alone tool to get insight into data distribution
 - As a preprocessing step for other algorithms

General Applications of Clustering



- Pattern Recognition
- Spatial Data Analysis
 - create thematic maps in GIS by clustering feature spaces
 - detect spatial clusters and explain them in spatial data mining
- Image Processing
- Economic Science (especially market research)
- WWW
 - Document classification
 - Cluster Weblog data to discover groups of similar access patterns

Examples of Clustering Applications

- Marketing: Help marketers discover distinct groups in their customer bases, and then use this knowledge to develop targeted marketing programs
- Land use: Identification of areas of similar land use in an earth observation database
- Insurance: Identifying groups of motor insurance policy holders with a high average claim cost
- City-planning: Identifying groups of houses according to their house type, value, and geographical location
- Earth-quake studies: Observed earth quake epicenters should be clustered along continent faults

What Is Good Clustering?

- A good clustering method will produce high quality clusters with
 - high intra-class similarity
 - low inter-class similarity
- The quality of a clustering result depends on both the similarity measure used by the method and its implementation.

Type of data in clustering analysis



- Interval-scaled variables:
- Binary variables:
- Nominal, ordinal, and ratio variables:
- Variables of mixed types:

Similarity and Dissimilarity Between Objects

- Distances are normally used to measure the similarity or dissimilarity between two data objects

Binary Variables

Nominal Variables

Ordinal Variables

Ratio-Scaled Variables

Categorization of Major Clustering Methods



1. Partitioning algorithms: Construct various partitions and then evaluate them by some criterion
2. Hierarchy algorithms: Create a hierarchical decomposition of the set of data (or objects) using some criterion
3. Density-based: based on connectivity and density functions
4. Grid-based: based on a multiple-level granularity structure
5. Model-based: A model is hypothesized for each of the clusters and the idea is to find the best fit of that model to each other

Partitioning method

Partitioning method: Construct a partition of a database D of n objects into a set of k clusters

- Given a k , find a partition of k clusters that optimizes the chosen partitioning criterion
 - Global optimal: exhaustively enumerate all partitions
 - Heuristic methods: k -means and k -medoids algorithms
 - k -means (MacQueen'67): Each cluster is represented by the center of the cluster
 - k -medoids or PAM (Partition around medoids) (Kaufman & Rousseeuw'87): Each cluster is represented by one of the objects in the cluster

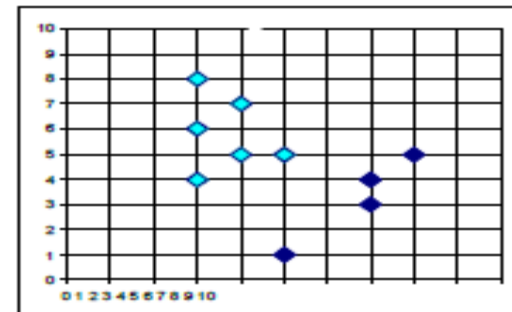
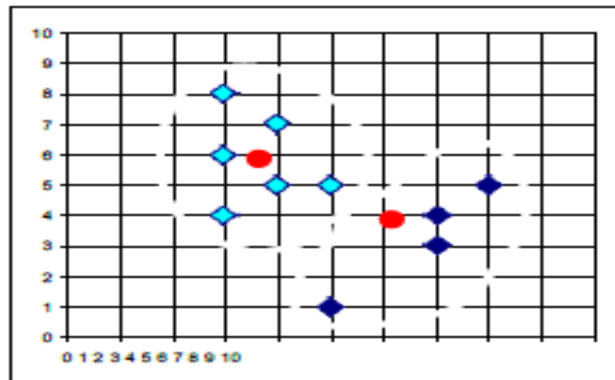
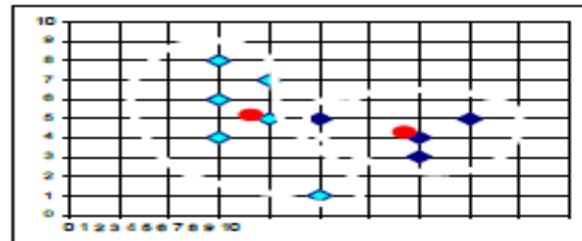
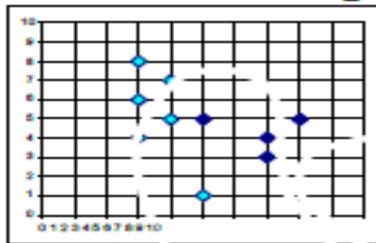
The *K*-Means Clustering Method

- Given k , the k -means algorithm is implemented in 4 steps:
 - Partition objects into k nonempty subsets
 - Compute seed points as the centroids of the clusters of the current partition.
The centroid is the center (mean point) of the cluster.
 - Assign each object to the cluster with the nearest seed point.
 - Go back to Step 2, stop when no more new assignment

The *K*-Means Clustering Method

The *K*-Means Clustering Method

- **Example**



Comments on the *K*-Means Method

Hierarchical Clustering

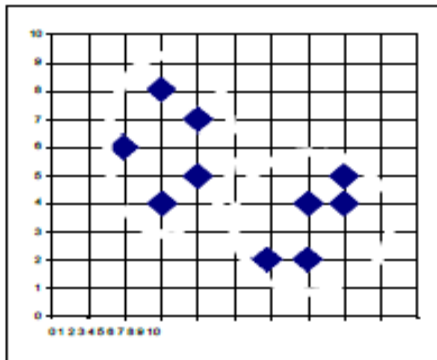
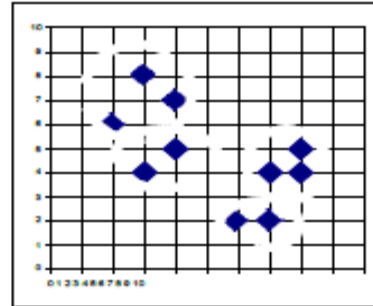
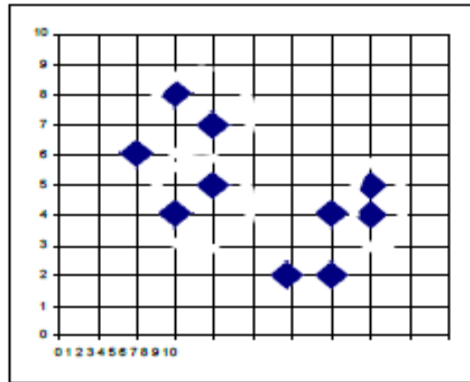
Use distance matrix as clustering criteria. This method does not require the number of clusters k

as an input, but needs a termination condition

AGNES (Agglomerative Nesting)

- *Introduced in Kaufmann and Rousseeuw (1990)*
- *Implemented in statistical analysis packages, e.g., Splus*
- *Use the Single-Link method and the dissimilarity matrix.*
- *Merge nodes that have the least dissimilarity*
- *Go on in a non-descending fashion*
- *Eventually all nodes belong to the same cluster*

AGNES (Agglomerative Nesting)



A Dendrogram Shows How the Clusters are Merged Hierarchically

DIANA (Divisive Analysis)



DIANA (Divisive Analysis)

- Introduced in Kaufmann and Rousseeuw (1990)
- Implemented in statistical analysis packages, e.g., Splus
- Inverse order of AGNES
- Eventually each node forms a cluster on its own

AGGLOMERATIVE HIERARCHICAL CLUSTERING

- Algorithms of hierarchical cluster analysis are divided into the two categories divisible algorithms and agglomerative algorithms.
- A divisible algorithm starts from the entire set of samples X and divides it into a partition of subsets, then divides each subset into smaller sets, and so on.
- Thus, a divisible algorithm generates a sequence of partitions that is ordered from a coarser one to a finer one. An agglomerative algorithm first regards each object as an initial cluster.
- The clusters are merged into a coarser partition, and the merging process proceeds until the trivial partition is obtained: all objects are in one large cluster.

Hierarchical and Non-Hierarchical Clustering

- There are two main types of clustering techniques, those that create a hierarchy of clusters and those that do not.
- The hierarchical clustering techniques create a hierarchy of clusters from small to big. The main reason for this is that, as was already stated, clustering is an unsupervised learning technique, and as such, there is no absolutely correct answer.
- For this reason and depending on the particular application of the clustering, fewer or greater numbers of clusters may be desired. With a hierarchy of clusters defined it is possible to choose the number of clusters that are desired.
- At the extreme it is possible to have as many clusters as there are records in the database.
- In this case the records within the cluster are optimally similar to each other (since there is only one) and certainly different from the other clusters.

Density-Based Clustering Methods



- Clustering based on density (local cluster criterion), such as density-connected points
- Major features:
 - Discover clusters of arbitrary shape
 - Handle noise
 - One scan
 - Need density parameters as termination condition
- Several interesting studies:
 - DBSCAN: Ester, et al. (KDD'96)
 - OPTICS: Ankerst, et al (SIGMOD'99).
 - DENCLUE: Hinneburg & D. Keim (KDD'98)
 - CLIQUE: Agrawal, et al. (SIGMOD'98)

DBSCAN: Density Based Spatial Clustering of Applications with Noise



DBSCAN: Density Based Spatial Clustering of Applications with Noise

- Relies on a *density-based notion of cluster: A cluster is defined as a maximal set of density-connected points*
- Discovers clusters of arbitrary shape in spatial databases with noise

DBSCAN: The Algorithm

- Arbitrary select a point p
- Retrieve all points density-reachable from p wrt Eps and $MinPts$.
- If p is a core point, a cluster is formed.
- If p is a border point, no points are density-reachable from p and DBSCAN visits the next point of the database.
- Continue the process until all of the points have been processed

OPTICS: A Cluster-Ordering Method (1999)



OPTICS: A Cluster-Ordering Method (1999)

- OPTICS: Ordering Points To Identify the Clustering Structure
 - Ankerst, Breunig, Kriegel, and Sander (SIGMOD'99)
 - Produces a special order of the database wrt its density-based clustering structure
 - This cluster-ordering contains info equiv to the density-based clusterings corresponding to a broad range of parameter settings
 - Good for both automatic and interactive cluster analysis, including finding intrinsic clustering structure
 - Can be represented graphically or using visualization techniques

Denclue: Technical Essence

Denclue: Technical Essence

- Uses grid cells but only keeps information about grid cells that do actually contain data points and manages these cells in a tree-based access structure.
- Influence function: describes the impact of a data point within its neighborhood.
- Overall density of the data space can be calculated as the sum of the influence function of all data points.
- Clusters can be determined mathematically by identifying density attractors.
- Density attractors are local maximal of the overall density function.

Grid-Based Methods

Using multi-resolution grid data structure

- Several interesting methods
 - STING (a Statistical Information Grid approach) by Wang, Yang and Muntz (1997)
 - WaveCluster by Sheikholeslami, Chatterjee, and Zhang (VLDB'98)
- A multi-resolution clustering approach using wavelet method
 - CLIQUE: Agrawal, et al. (SIGMOD'98)

Grid-Based Methods

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STING: A Statistical Information Grid Approach

STING: A Statistical Information Grid Approach

- Wang, Yang and Muntz (VLDB'97)
- The spatial area is divided into rectangular cells
- There are several levels of cells corresponding to different levels of resolution

STING: A Statistical Information Grid Approach (2)

- Each cell at a high level is partitioned into a number of smaller cells in the next lower level
- Statistical info of each cell is calculated and stored beforehand and is used to answer queries
- Parameters of higher level cells can be easily calculated from parameters of lower level cell
 - *count, mean, s, min, max*
 - type of distribution—normal, *uniform, etc.*
- Use a top-down approach to answer spatial data queries
- Start from a pre-selected layer—typically with a small number of cells
- For each cell in the current level compute the confidence interval

Model-Based Clustering Methods



Model-Based Clustering Methods:

1. Attempt to optimize the fit between the data and some mathematical model
2. Statistical and AI approach Conceptual clustering
3. A form of clustering in machine learning
4. Produces a classification scheme for a set of unlabeled objects
5. Finds characteristic description for each concept (class) COBWEB (Fisher'87)
6. A popular a simple method of incremental conceptual learning
7. Creates a hierarchical clustering in the form of a classification tree
8. Each node refers to a concept and contains a probabilistic description of that concept

1. Neural network approaches

- a. Represent each cluster as an exemplar, acting as a —prototype of the cluster
- b. New objects are distributed to the cluster whose exemplar is the most similar according to some distance measure

2. Competitive learning

- a. Involves a hierarchical architecture of several units (neurons)
- b. Neurons compete in a —winner-takes-all fashion for the object currently being presented

Model-Based Clustering Methods



- Attempt to optimize the fit between the data and some mathematical model
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 - Conceptual clustering
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COBWEB Clustering Method

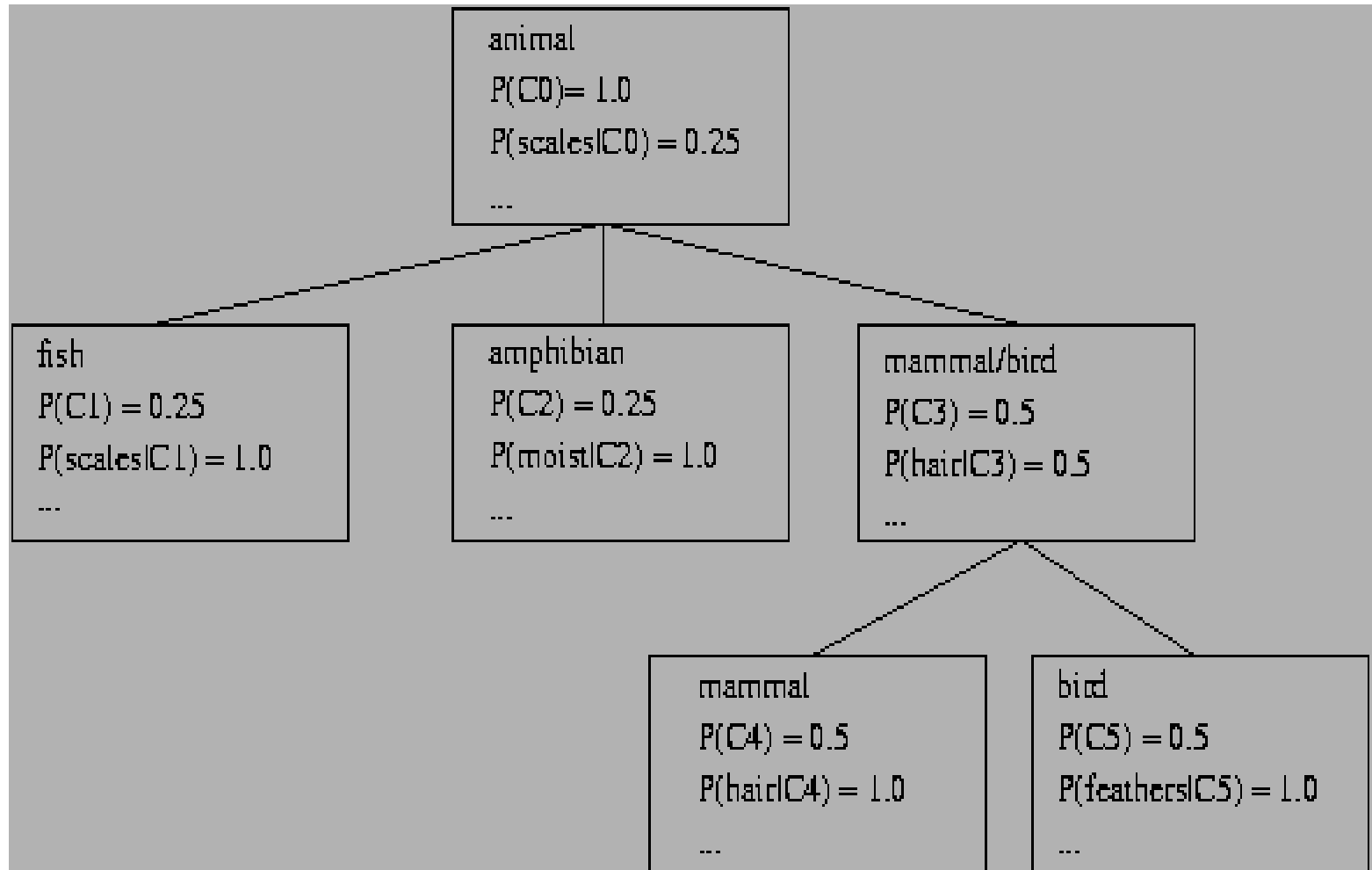


Fig. A classification tree

What Is Outlier Discovery?

- What are outliers?
 - The set of objects are considerably dissimilar from the remainder of the data
 - Example: Sports: Michael Jordon, Wayne Gretzky, ...
- Problem
 - Find top n outlier points
- Applications:
 - Credit card fraud detection
 - Telecom fraud detection
 - Customer segmentation
 - Medical analysis

Outlier Discovery: Statistical Approaches

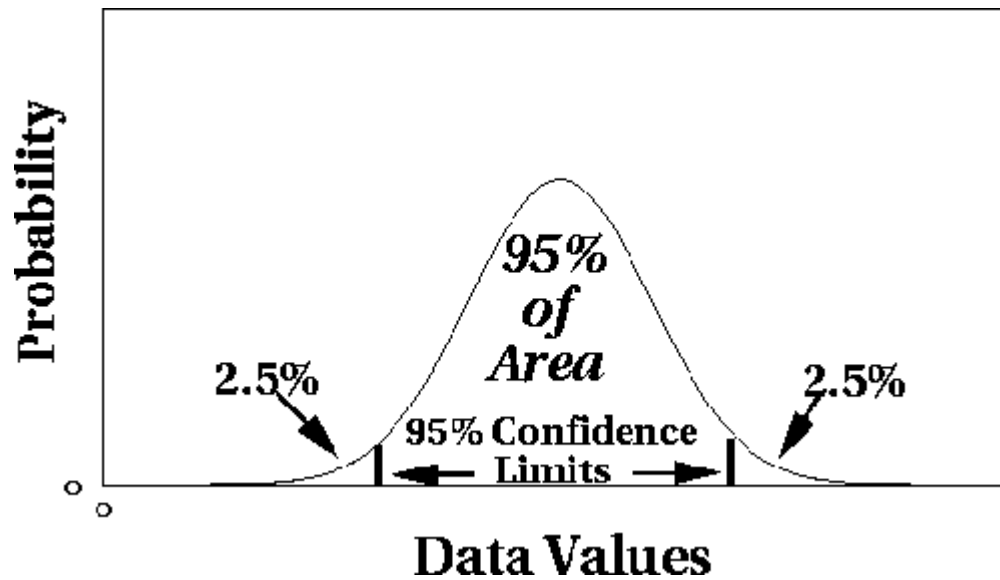


Fig. Outlier Discovery: Statistical Approaches

Outlier Discovery: Distance-Based Approach

- Introduced to counter the main limitations imposed by statistical methods
 - We need multi-dimensional analysis without knowing data distribution.
- Distance-based outlier: A $DB(p, D)$ -outlier is an object O in a dataset T such that at least a fraction p of the objects in T lies at a distance greater than D from O
- Algorithms for mining distance-based outliers
 - Index-based algorithm
 - Nested-loop algorithm
 - Cell-based algorithm

Outlier Discovery: Deviation-Based Approach

- Identifies outliers by examining the main characteristics of objects in a group
- Objects that —deviate from this description are considered outliers
- sequential exception technique
 - simulates the way in which humans can distinguish unusual objects from among a series of supposedly like objects
- OLAP data cube technique
 - uses data cubes to identify regions of anomalies in large multidimensional data