# Scientific Data Analysis: Apriori and Data Warehouses

Jarek Szlichta

http://data.science.uoit.ca/

Acknowledgments: Jiawei Han, Micheline Kamber and Jian Pei, Data Mining - Concepts and Techniques

# Apriori Technique

- Frequent Itemset Mining Methods
  - Apriori
- Which Patterns Are Interesting?
- Summary

# What Is Frequent Pattern Analysis?

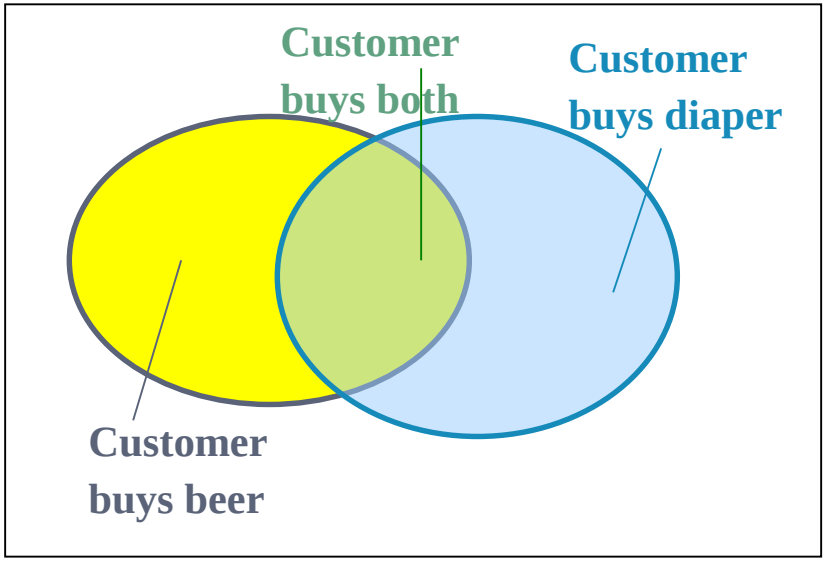
- Frequent pattern: a pattern (a set of items) that occurs frequently in a data set
- Motivation: Finding inherent regularities in data
  - What products were often purchased together?— Beer and diapers?!
  - What kinds of DNA are sensitive to this new drug?
  - Can we automatically classify web documents?
- Applications
  - Basket data analysis, cross-marketing, catalog design, sale campaign analysis, Web log (click stream) analysis, and DNA sequence analysis.

# Why Is Frequent Pattern Mining Important?

- Foundation for many essential data mining tasks
  - Association and correlation analysis
  - Structural (e.g., sub-graph) patterns
  - Time-series, and stream data
  - Cluster analysis: frequent pattern-based clustering
  - Data warehousing

# Basic Concepts: Frequent Patterns

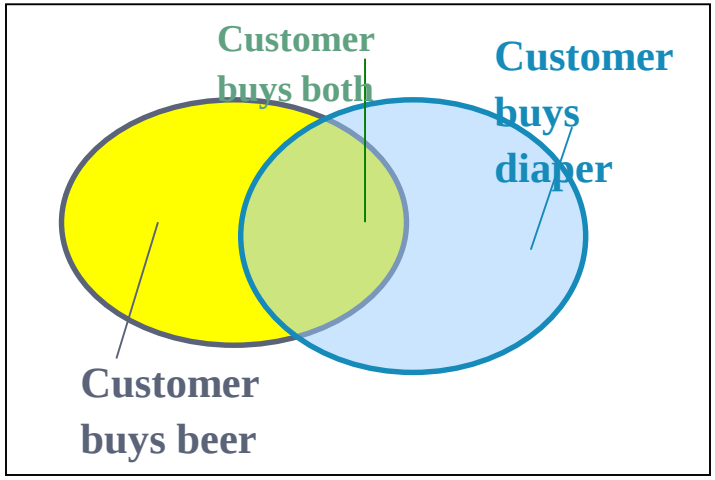
| Tid | Items bought |
|---|---|
| 10 | Beer, Nuts, Diaper |
| 20 | Beer, Coffee, Diaper |
| 30 | Beer, Diaper, Eggs |
| 40 | Nuts, Eggs, Milk |
| 50 | Nuts, Coffee, Diaper, Eggs, Milk |




- itemset: A set of one or more items
- k-itemset X = $\{x_1, \ldots, x_k\}$
  - e.g., 2-itemset {Beer, Diaper}
- *(absolute) support*, or, *support count* of X: Frequency or occurrence of an itemset X
  - e.g., absolute support for {Beer, Diaper} equals 3
- *(relative) support*, *s*, is the fraction of transactions that contains X (i.e., the probability that a transaction contains X)
  - e.g., relative support for {Beer, Diaper} equals 3/5
- An itemset X is *frequent* if X's support is no less than a *minsup* threshold
  - e.g., assume minsup = 2 (40%). Then, for instance, {Beer, Diaper} (support 3), {Milk, Eggs, Nuts} (support 2) are frequent itemset patterns.

# Basic Concepts: Association Rules

| Tid | Items bought |
|---|---|
| 10 | Beer, Nuts, Diaper |
| 20 | Beer, Coffee, Diaper |
| 30 | Beer, Diaper, Eggs |
| 40 | Nuts, Eggs, Milk |
| 50 | Nuts, Coffee, Diaper, Eggs, Milk |




- 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 minsup = 50%, minconf = 50%*

*Freq. Pat.:* Beer:3, Nuts:3, Diaper:4, Eggs:3, {Beer, Diaper}:3

- Association rules: (many more!)
  - *Beer* → *Diaper* (3/5 = 60%, 3/3 = 100%)
  - *Diaper* → *Beer* (3/5= 60%, 3/4 = 75%)

# Computational Complexity

- How many itemsets are potentially to be generated in the worst case?
  - The number of frequent itemsets to be generated is sensitive to the minsup threshold
  - When minsup is low, there exist potentially an exponential number of frequent itemsets
  - The worst case: $M^N$ where M: # distinct items, and N: max length of transactions

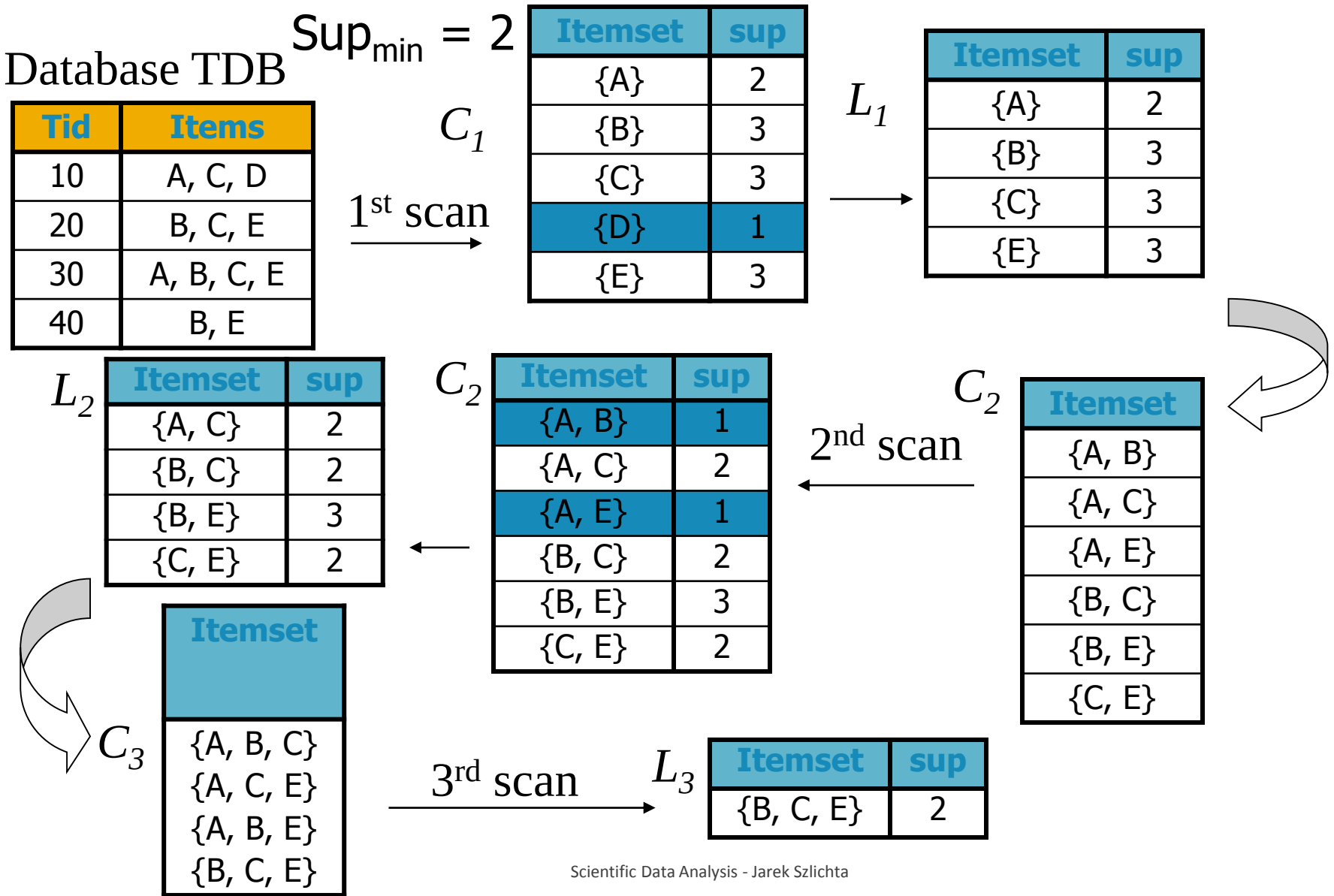
# The Downward Closure Property

- The downward closure property of frequent patterns
  - Any subset of a frequent itemset must be frequent
  - If **{milk, eggs, nuts}** is frequent, so is **{milk, eggs}**
  - i.e., every transaction having {milk, eggs, nuts} also contains {milk, eggs}

# Apriori: A Candidate Generation & Test Approach

- Apriori pruning principle: If there is any itemset which is infrequent, its superset should not be generated/tested!
- Method:
  - Initially, scan DB once to get frequent 1-itemset
  - Generate length (k+1) candidate itemsets from length k and length 1 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

$L_1$ = {frequent items};

**for** ($k$ = 1; $L_k$ !=∅; $k$++) **do begin**

  $C_{k+1}$ = candidates generated from $L_k$ *and* $L_1$;

  **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** $\cup_k L_k$;

# Implementation of Apriori

- How to generate candidates?
  - Step 1: joining $L_k$ and $L_1$
  - Pruning
- Example of Candidate-generation
  - $L_3$={*abc, abd, acd, ace, bcd*}
  - Joining: $L_3 * L_1$
    - *e.g., abce etc.*
  - Pruning:
    - Assume d is not in $L_1$
    - *abcd* is not a candiate because *d* is not in $L_1$
  - $C_4$ = {*abce, ...*}

# Frequent Pairs in SQL

- Baskets(TID, item)

```
SELECT b1.item, b2.item
FROM Baskets b1, Baskets b2
WHERE b1.TID = b2.TID
  AND b1.item < b2.item
GROUP BY b1.item, b2.item
HAVING COUNT(*) >= s;
```

Look for two Basket tuples with the same TID and different items. First item must precede second, so we don't count the same pair twice.

Create a group for each pair of items that appears in at least one basket.

Throw away pairs of items that do not appear at least *s* times.

# A-Priori Trick – (1)

- Straightforward implementation involves a join of a huge Baskets relation with itself.
- The *a-priori algorithm* speeds the query by recognizing that a pair of items {*i*, *j* } cannot have support *s* unless both {*i* } and {*j* } do.

# A-Priori Trick – (2)

- Use a materialized view (table) to hold only information about frequent items.

```
INSERT INTO Baskets1(TID, item)
SELECT * FROM Baskets
WHERE item IN (
    SELECT item FROM Baskets
    GROUP BY item
    HAVING COUNT(*) >= s
);
```

Items that appear in at least *s* baskets.

# Frequent Pairs in SQL (Apriori)

- Baskets1 (TID, item)

```
SELECT b1.item, b2.item
FROM Baskets1 b1, Baskets1 b2
WHERE b1.TID = b2.TID
  AND b1.item < b2.item
GROUP BY b1.item, b2.item
HAVING COUNT(*) >= s;
```

# A-Priori Algorithm

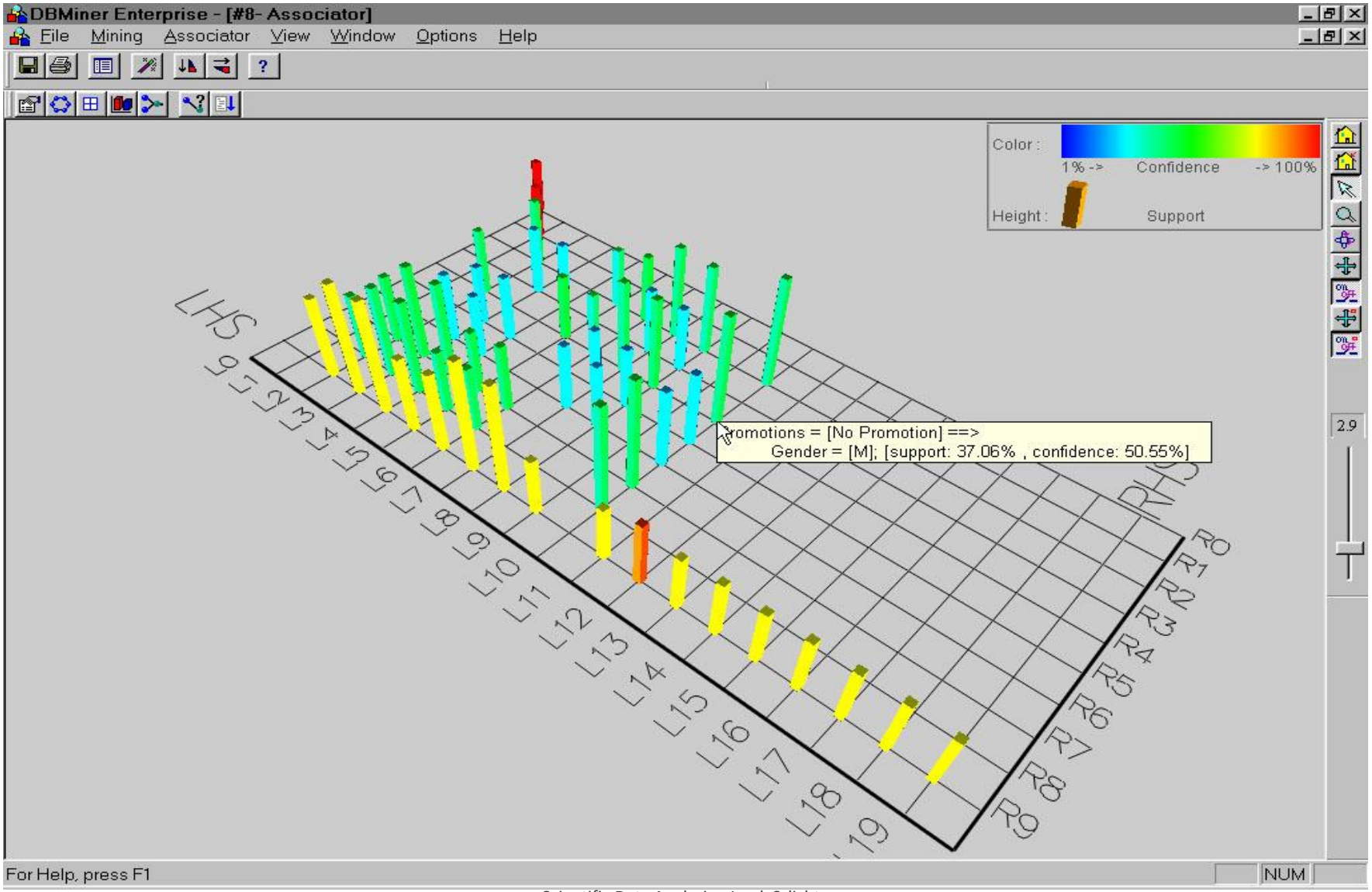
1. Materialize the view Baskets1.
2. Run the obvious query, but on Baskets1 instead of Baskets.

- Computing Baskets1 is cheap, since it does not involve a join.
- Baskets1 *probably* has many fewer tuples than Baskets.
  - Running time shrinks with the *square* of the number of tuples involved in the join.

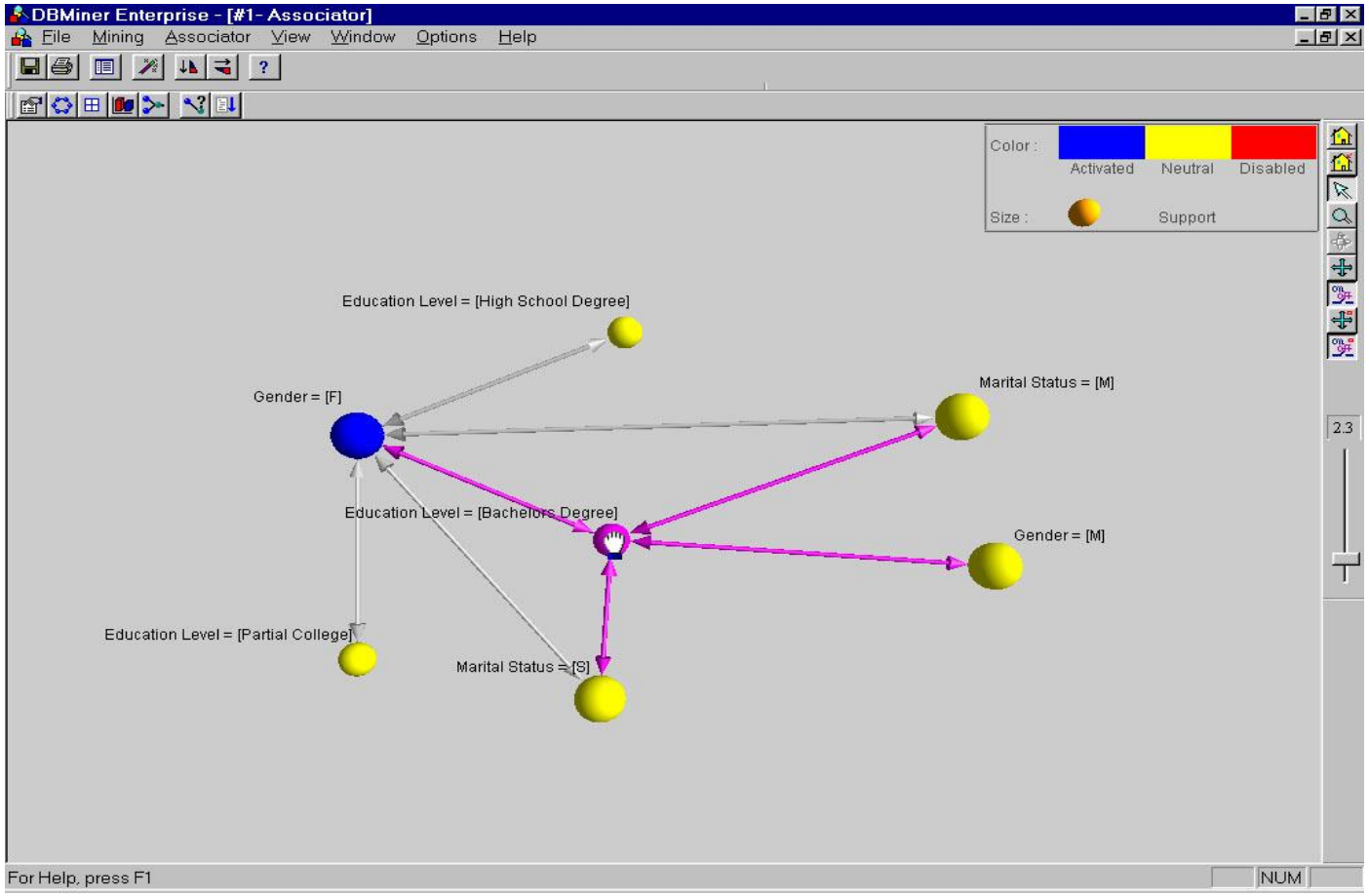
# Sampling for Frequent Patterns

- Select a *sample* of original database, mine frequent patterns within sample using Apriori
- Scan *entire* database once to verify frequent itemsets found in sample (to make sure they are actually frequent over entire dataset)

# Visualization of Association Rules: Plane Graph

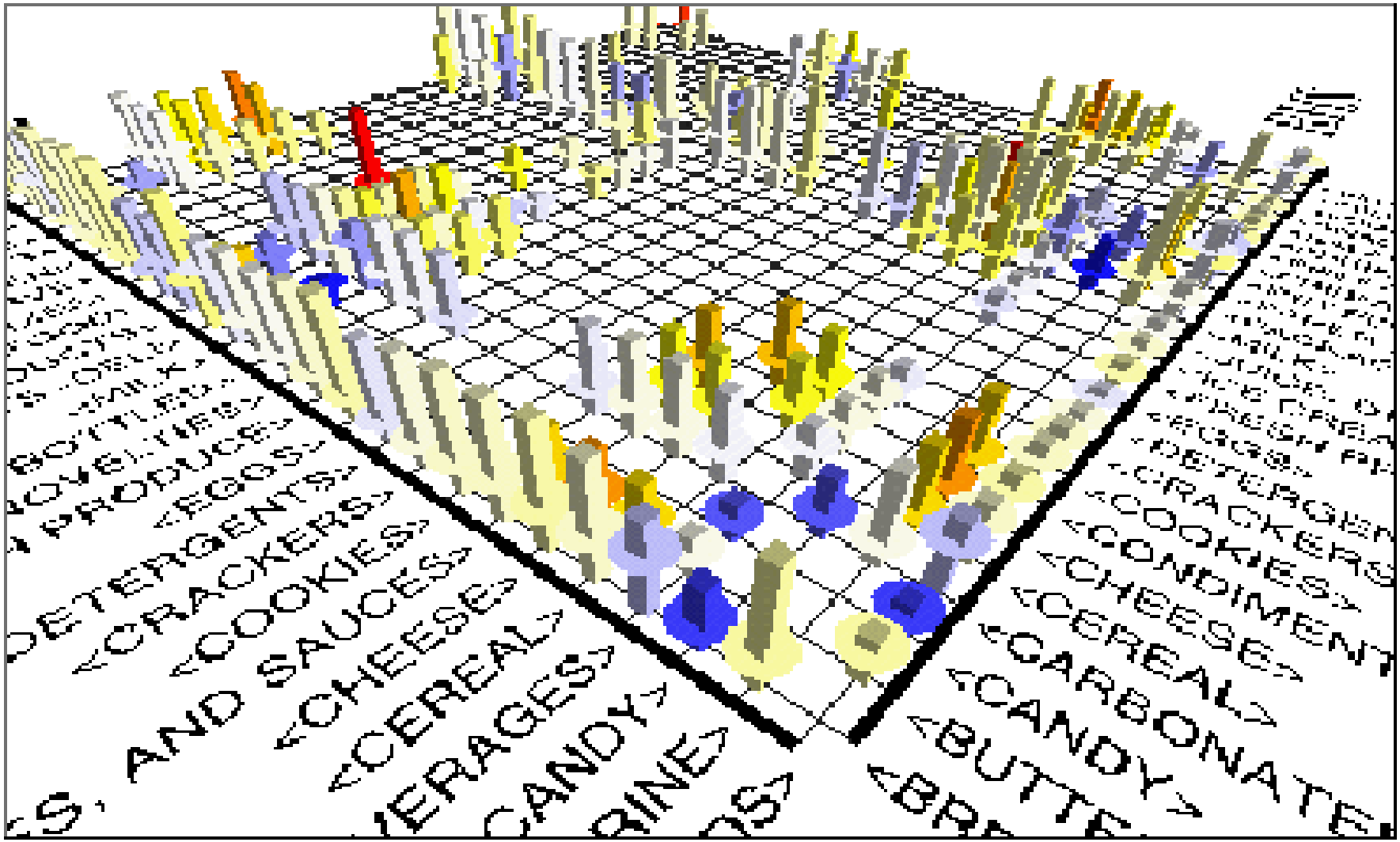


# Visualization of Association Rules: Rule Graph




- Items are visualized as balls
- Arrows indicate rule implication
- Size represents support

# Visualization of Association Rules (SGI/MineSet 3.0)



# Interestingness Measure: Correlations (Lift)

- *play basketball* $\Rightarrow$ *eat cereal* [40%, 66.7%] is misleading
  - The overall % of students eating cereal is 75%
- *play basketball* $\Rightarrow$ *not eat cereal* [20%, 33.3%] is more accurate, although with lower support and confidence
- Measure of dependent/correlated events: lift
  - Errata (They mess it up with the notation in the textbook)

$$lift = \frac{P(A \cap B)}{P(A)P(B)}$$

| | Basketball | Not basketball | Sum (row) |
|---|---|---|---|
| Cereal | 2000 | 1750 | 3750 |
| Not cereal | 1000 | 250 | 1250 |
| Sum(col.) | 3000 | 2000 | 5000 |

$$lift(Basketball, Cereal) = \frac{2000/5000}{3000/5000 * 3750/5000} = 0.89$$

$$lift(Basketball, \neg Cereal) = \frac{1000/5000}{3000/5000 * 1250/5000} = 1.33$$

# Summary

- Concepts: association rules, support-confident framework
- Scalable frequent pattern mining methods
  - Apriori (Candidate generation & test)
  - Sampling
- Which patterns are interesting?
  - Pattern evaluation methods

# Data Warehousing and On-line Analytical Processing

- Data Warehouse: Basic Concepts
- Data Warehouse Modeling: Data Cube and OLAP
- Data Warehouse Design and Usage
- Summary

# What is a Data Warehouse?

- Defined in many different ways.
  - 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

# 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)

# 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*

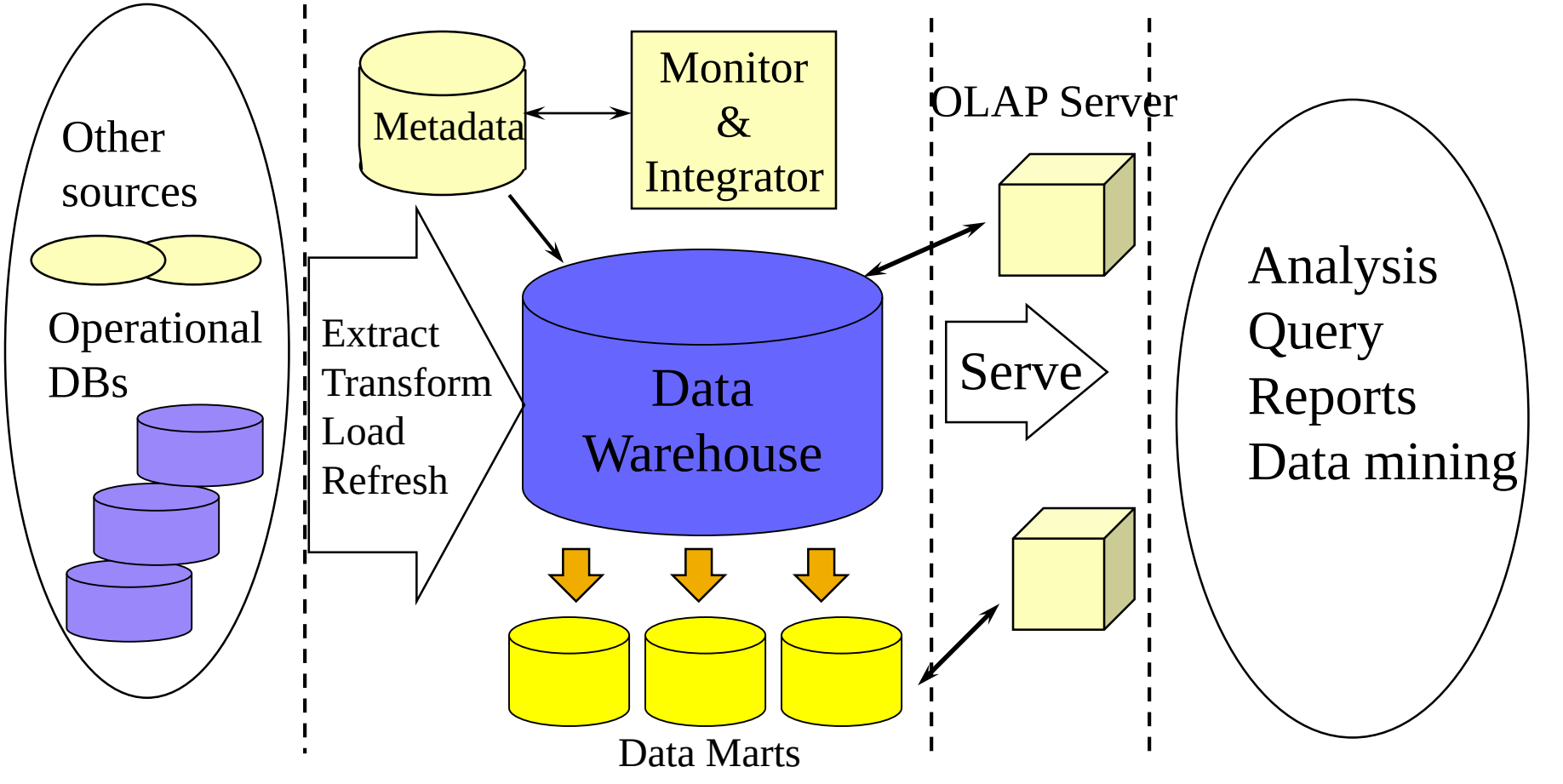
# OLTP vs. OLAP

| | 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<br>detailed, flat relational<br>isolated | historical,<br>summarized, multidimensional<br>integrated, consolidated |
| **usage** | repetitive | ad-hoc |
| **access** | read/write<br>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 (Operational Transaction Processing): access methods, indexing, concurrency control, recovery
  - Warehouse—tuned for OLAP (Online Analytical Processing): 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: Decision support 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

# Data Warehouse: A Multi-Tiered Architecture



# 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
- Virtual warehouse
  - A set of views over operational databases
  - Only some of the possible summary views may be materialized

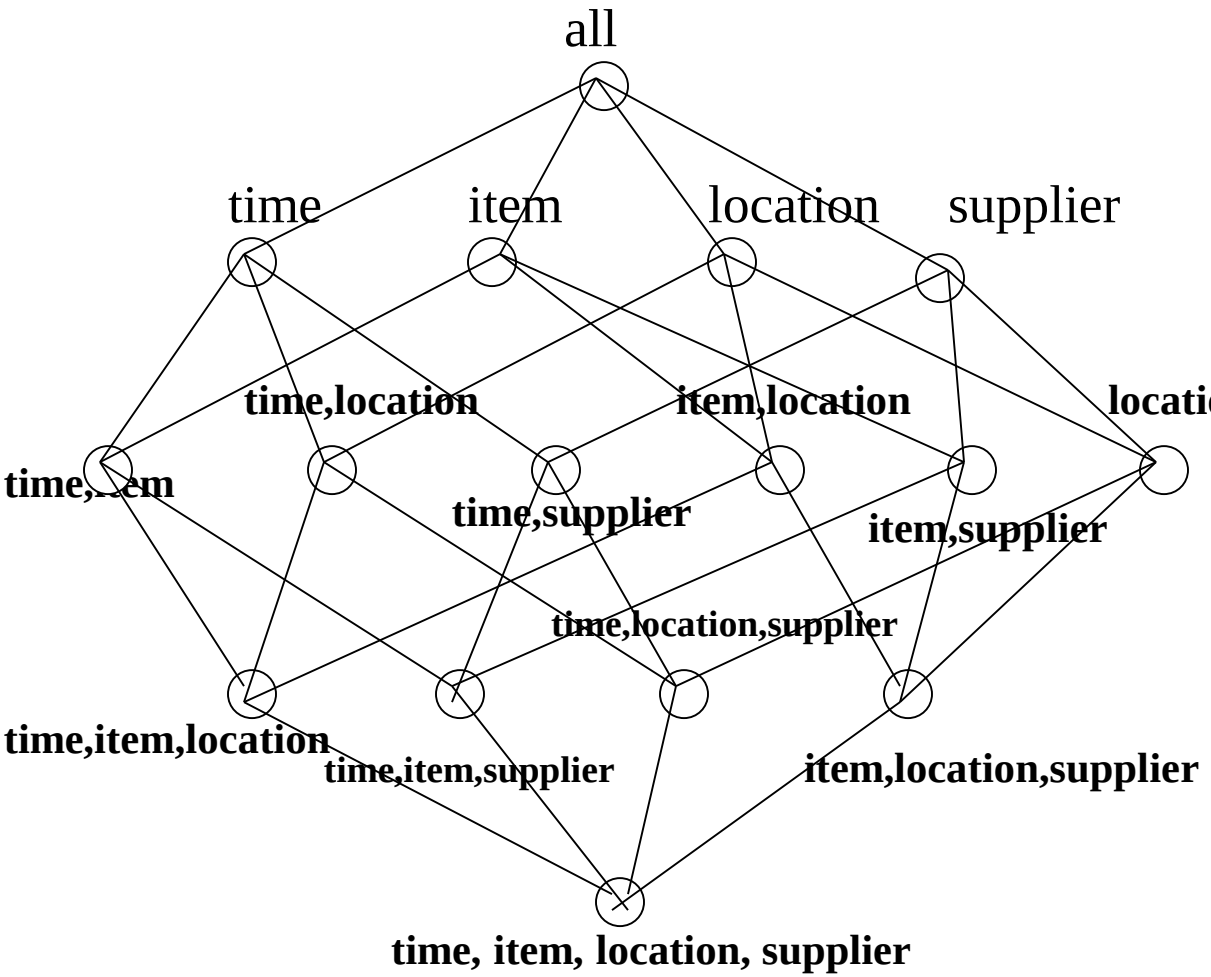
# Extraction, Transformation, and Loading (ETL)

- **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 indicies and partitions
- **Refresh**
  - propagate the updates from the data sources to the warehouse

# 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 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**, such as sales 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.

# Cube: A Lattice of Cuboids




0-D (*apex*) cuboid

1-D cuboids

2-D cuboids

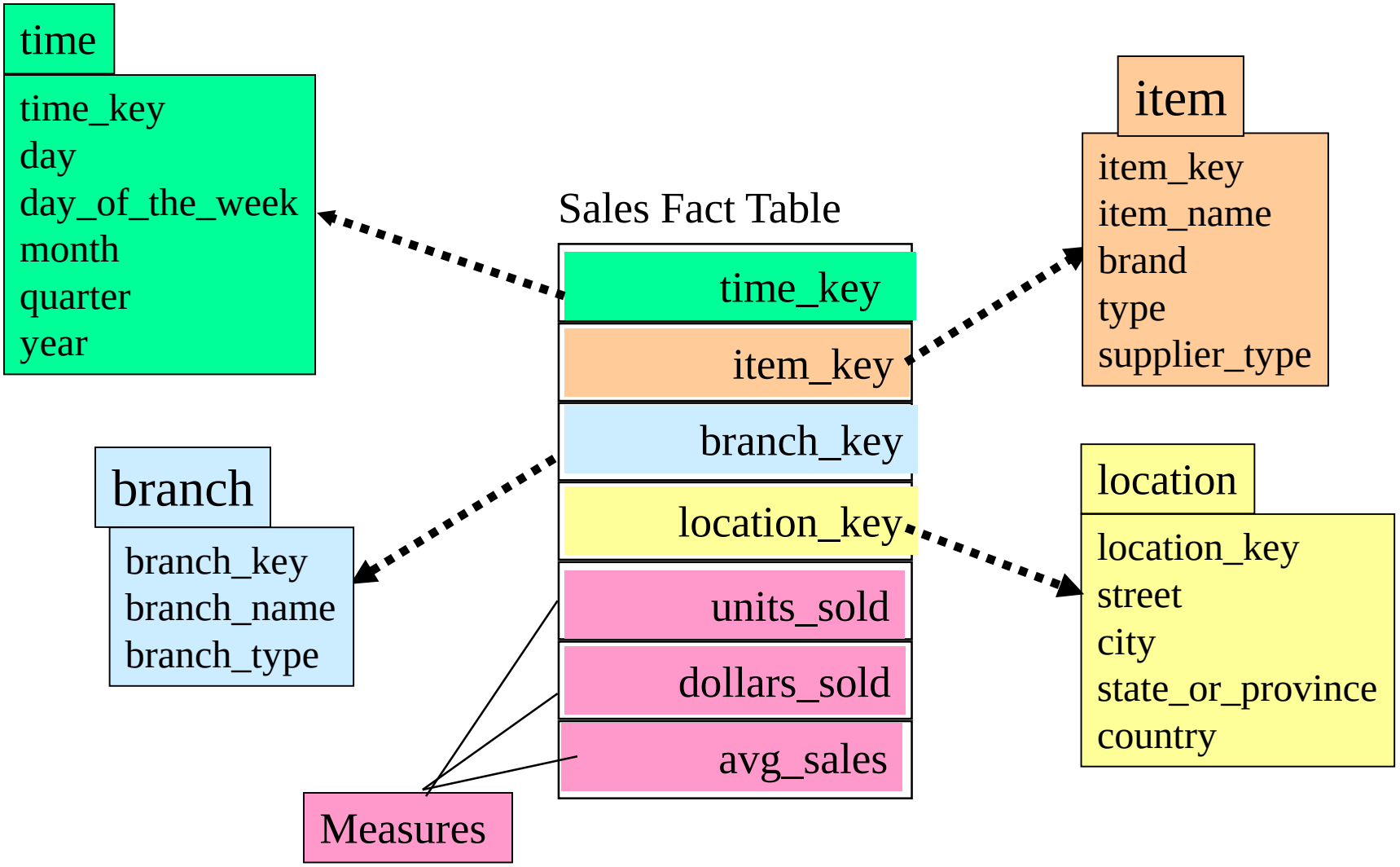
3-D cuboids

4-D (*base*) cuboid

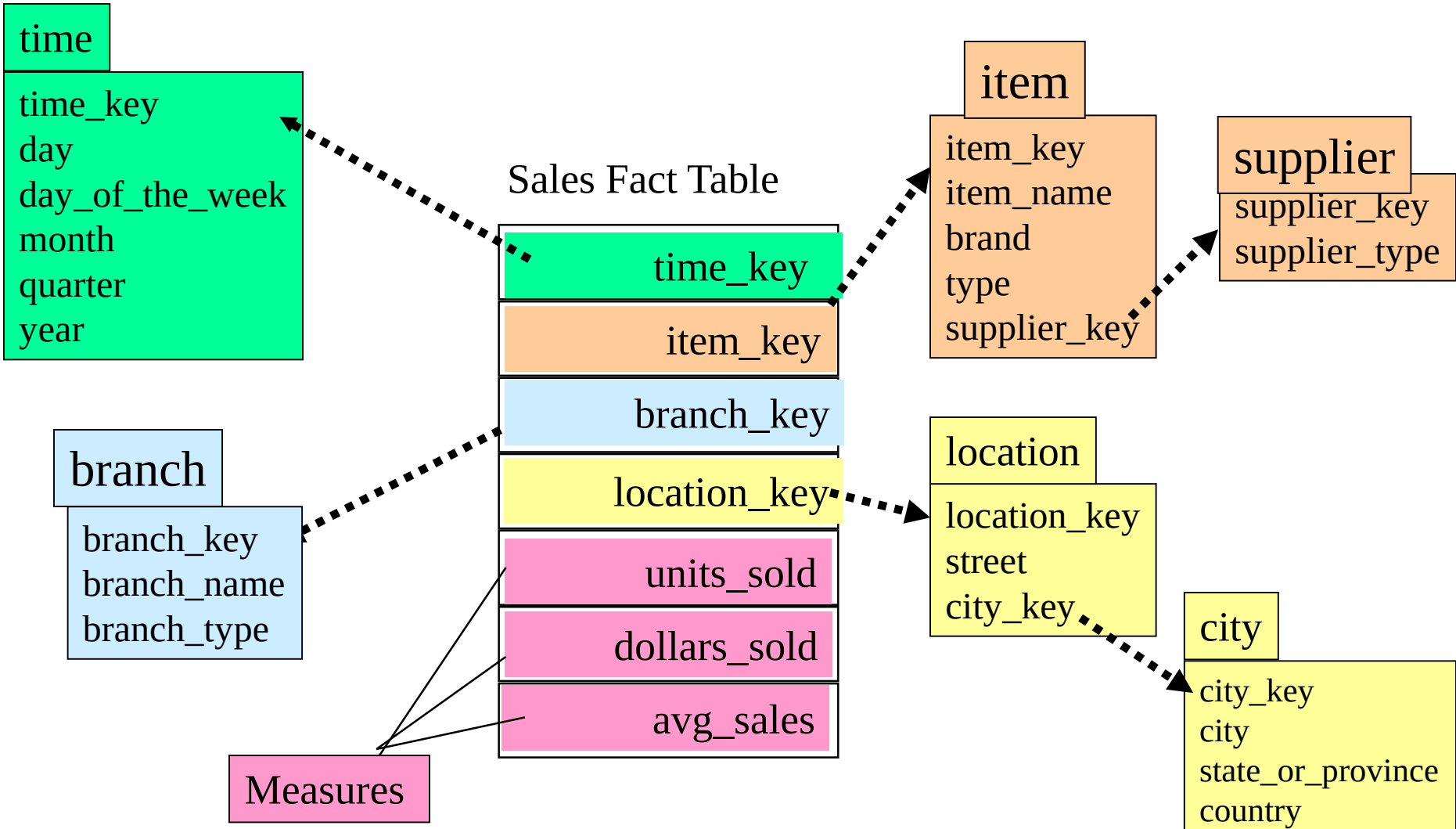
# Conceptual Modeling of Data Warehouses

- 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

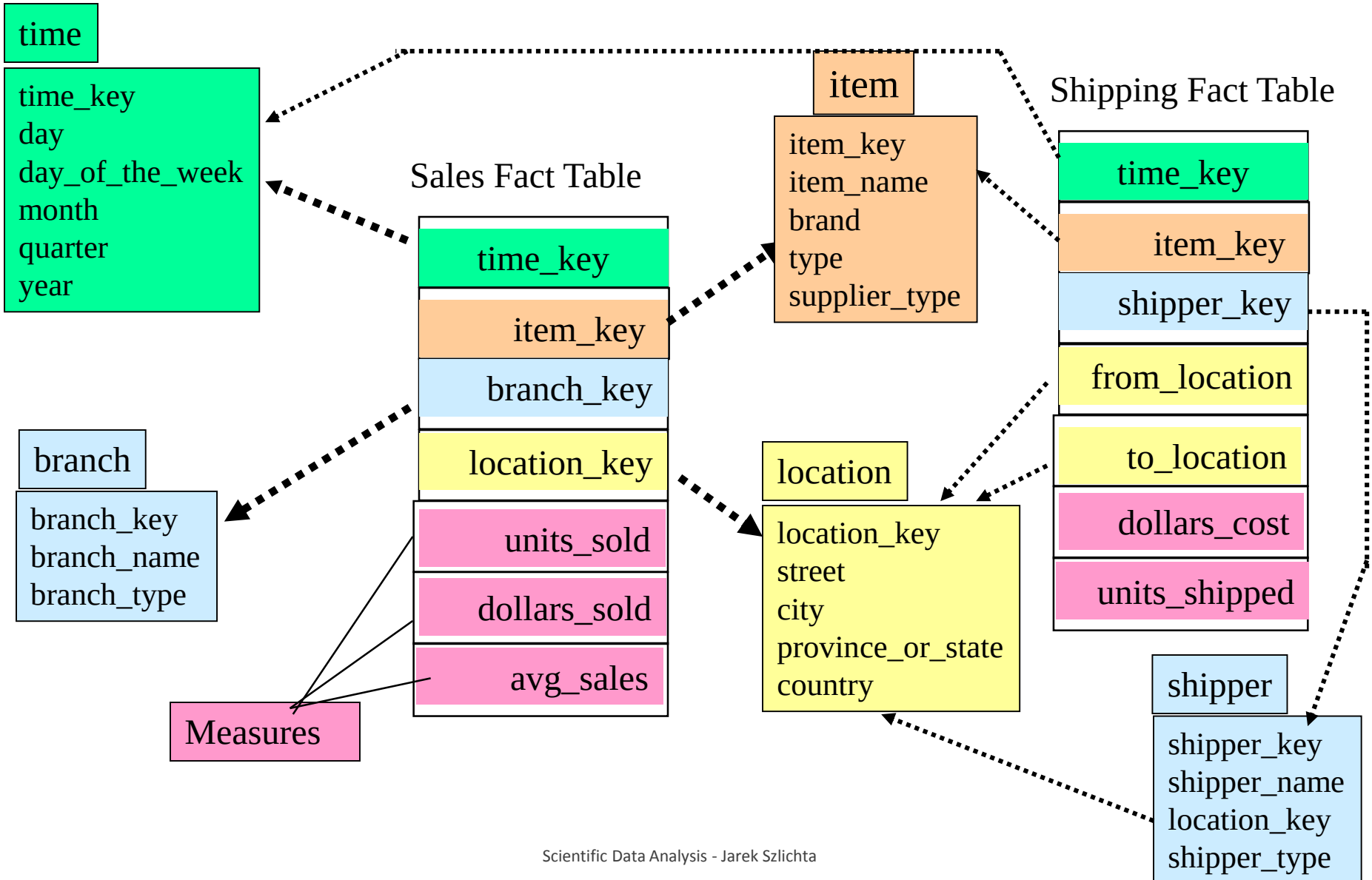
# Example of Star Schema



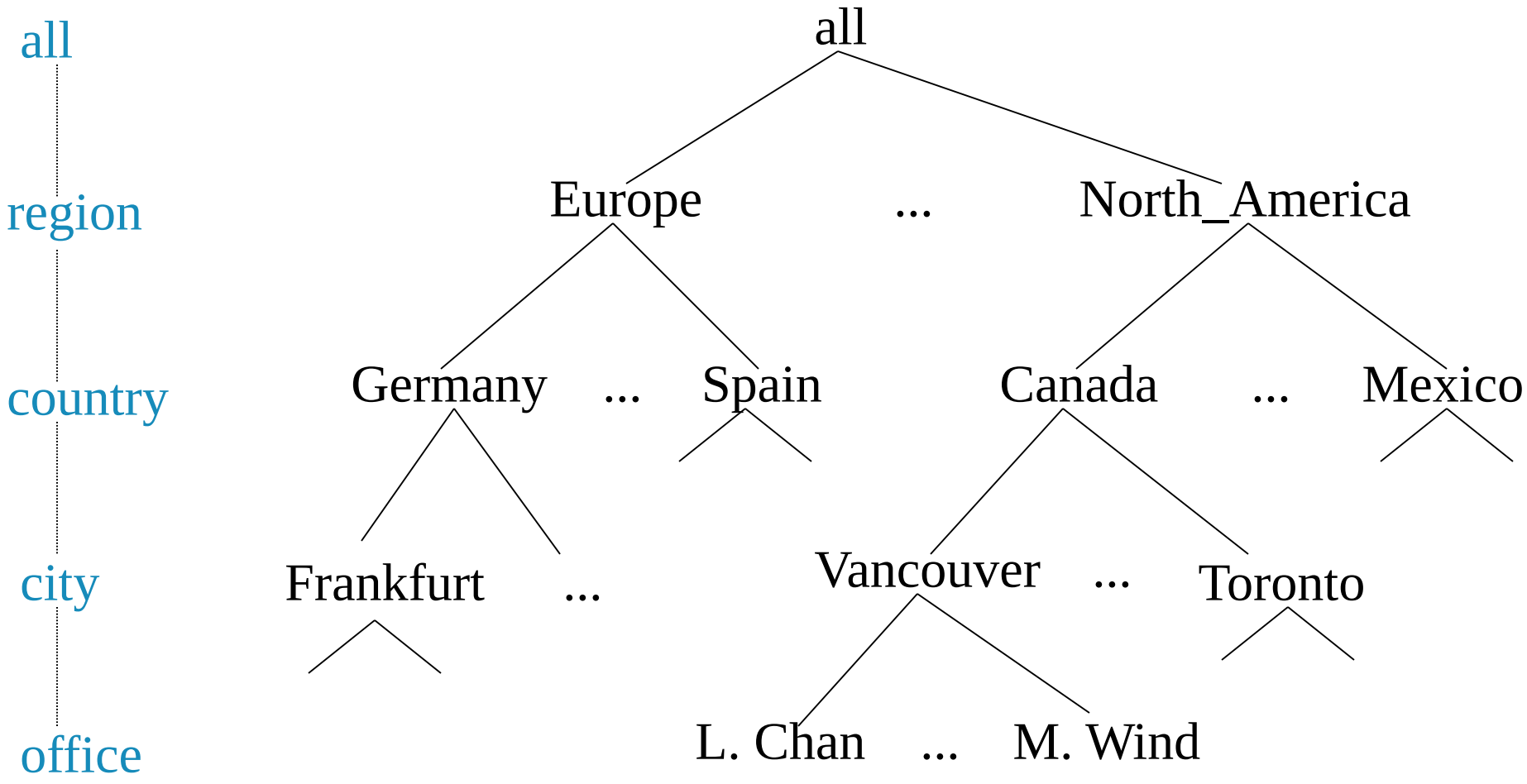
# Example of Snowflake Schema



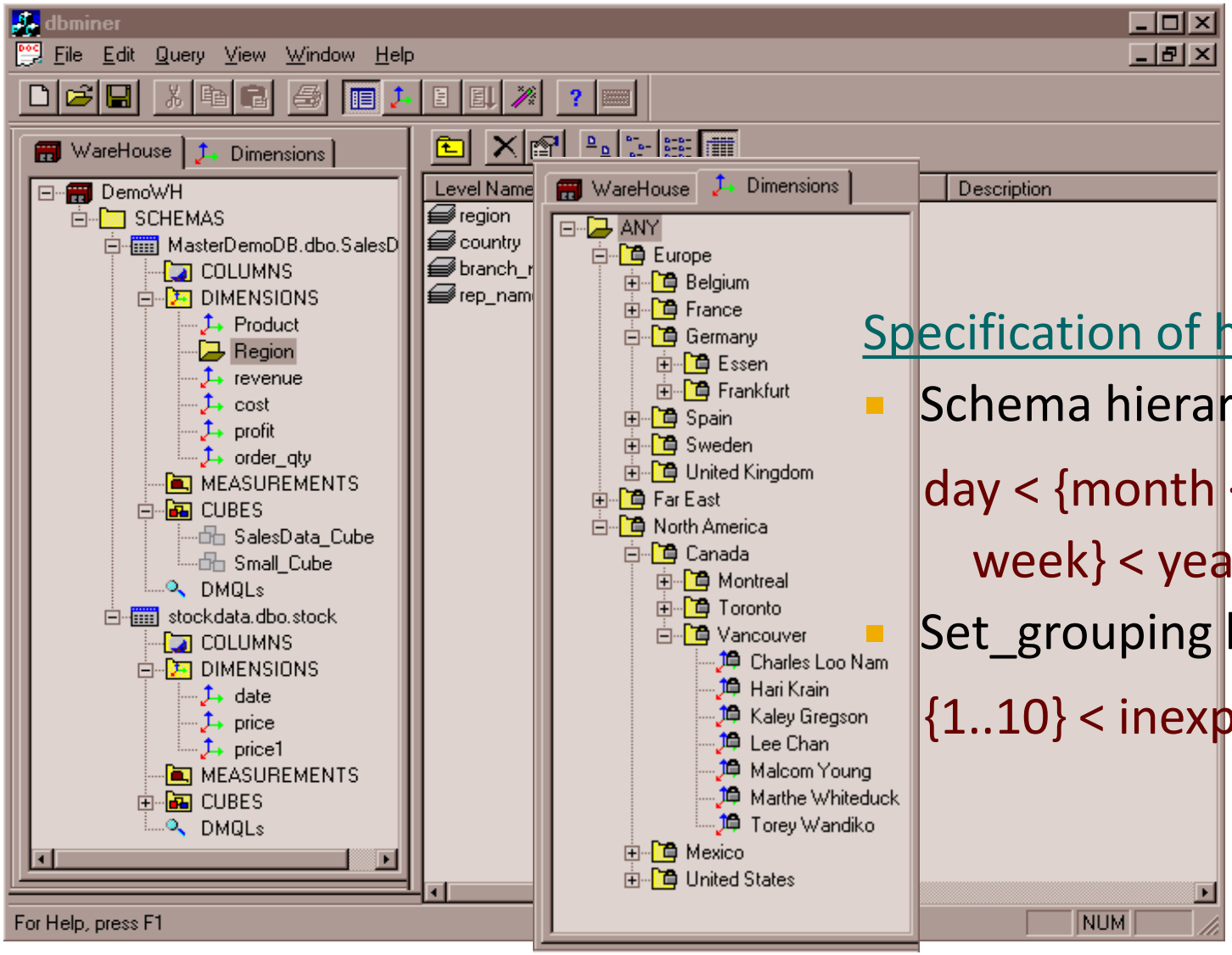
# Example of Fact Constellation



# A Concept Hierarchy: Dimension (location)



# View of Warehouses and Hierarchies




## Specification of hierarchies

- Schema hierarchy

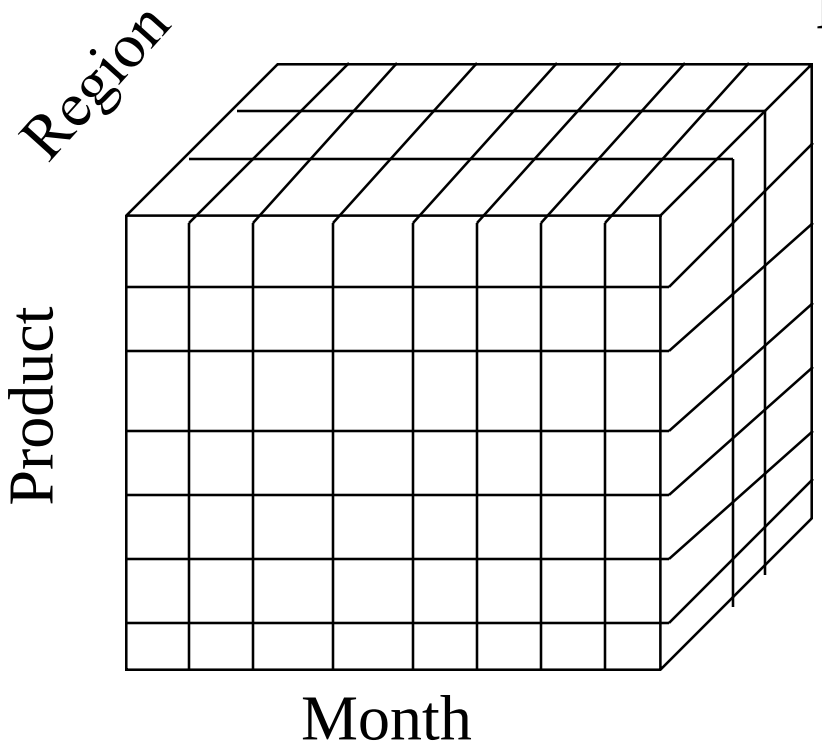
  day < {month < quarter; week} < year

- Set_grouping hierarchy

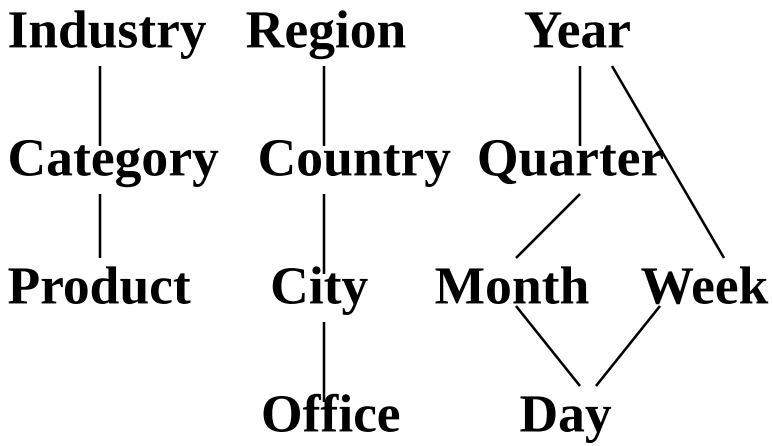
  {1..10} < inexpensive

# Multidimensional Data

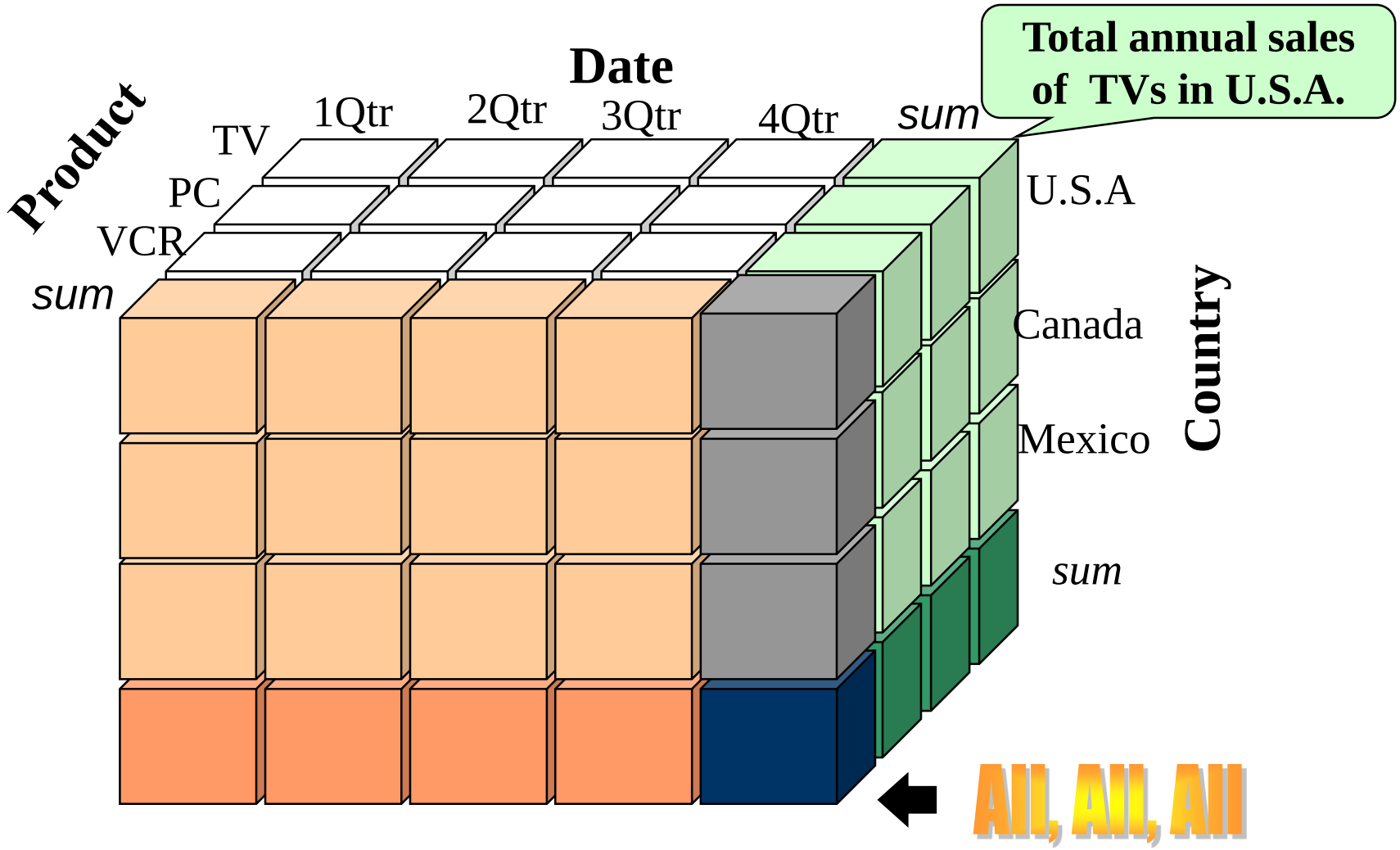
- Sales volume as a function of product, month, and region



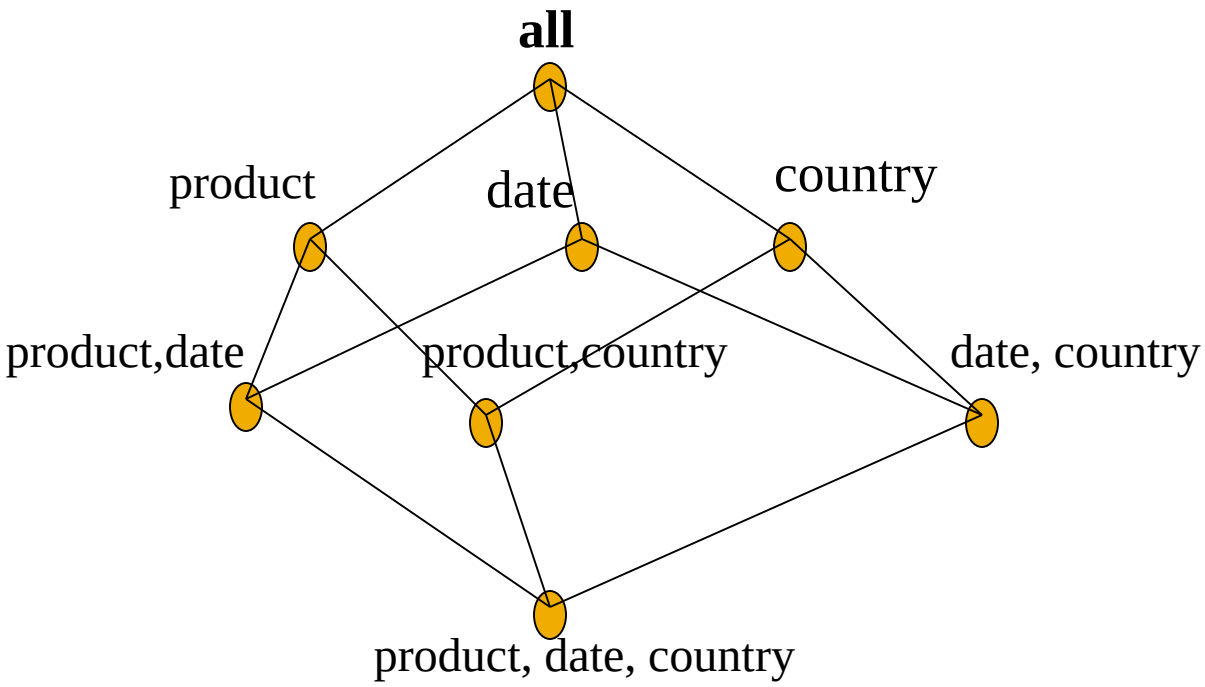

**Dimensions: *Product, Location, Time***
**Hierarchical summarization paths**



# A Sample Data Cube



# Cuboids Corresponding to the Cube




0-D (*apex*) cuboid

1-D cuboids

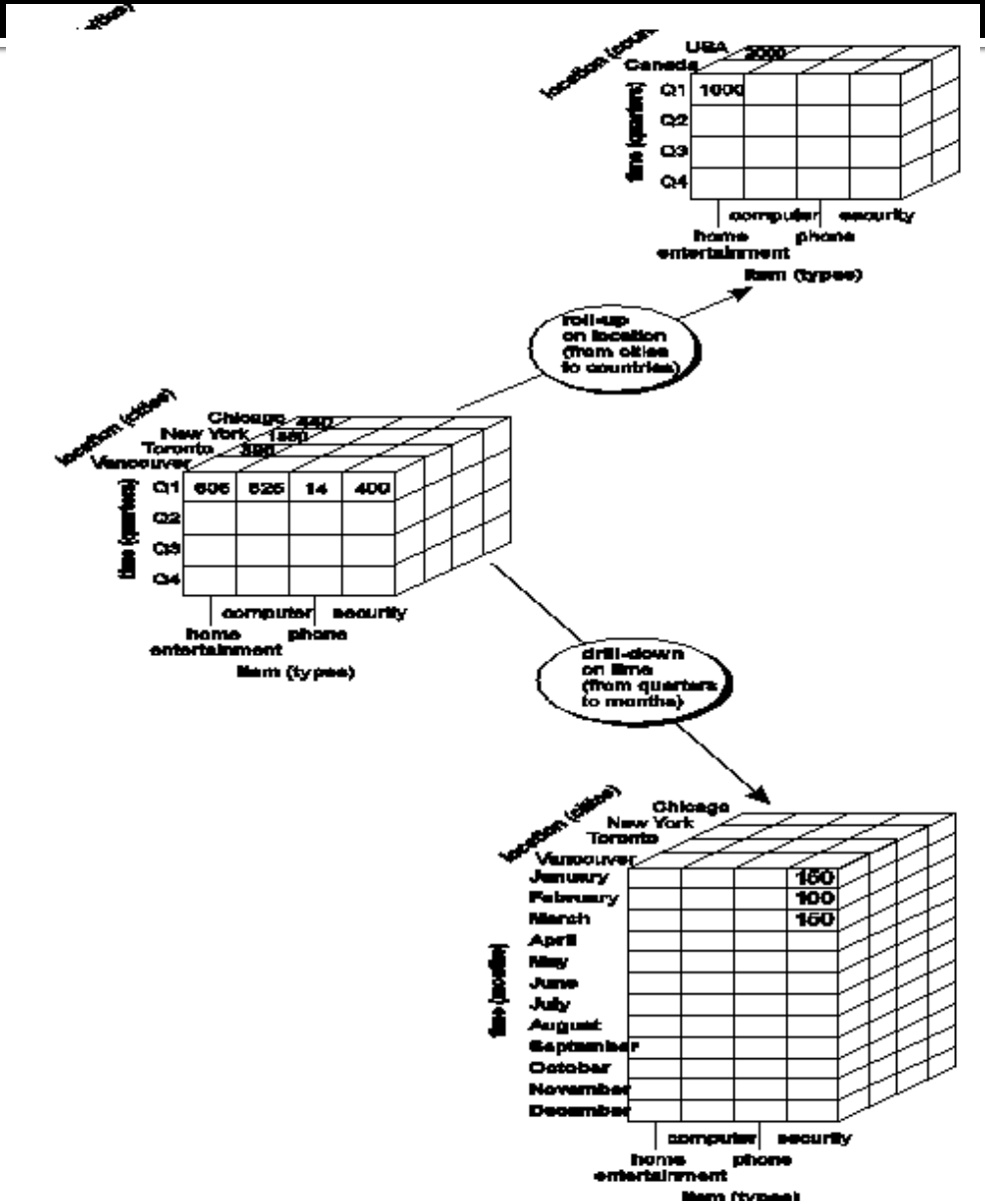
2-D cuboids

3-D (*base*) cuboid

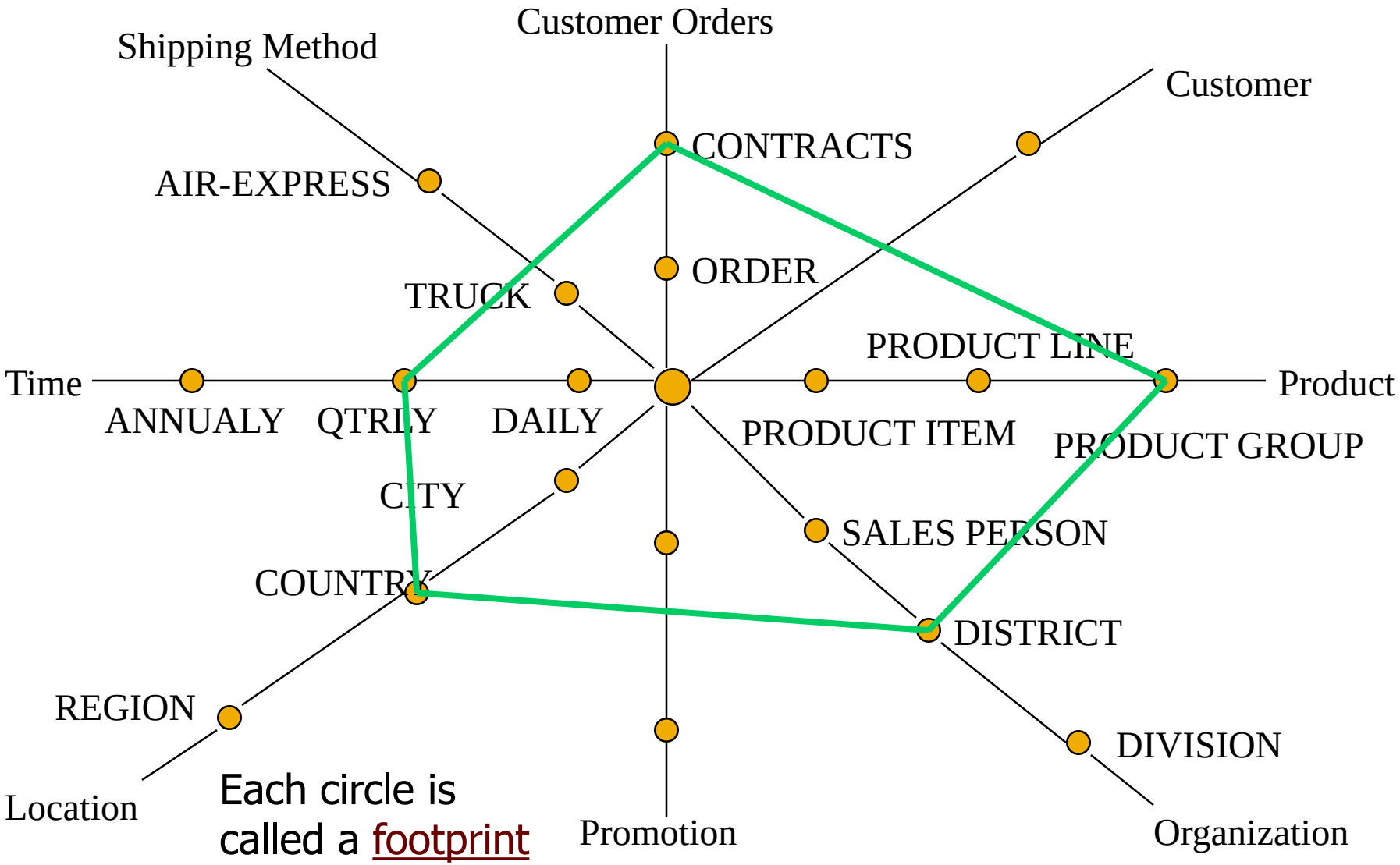
# Typical OLAP Operations

- 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*

# Typical OLAP Operations

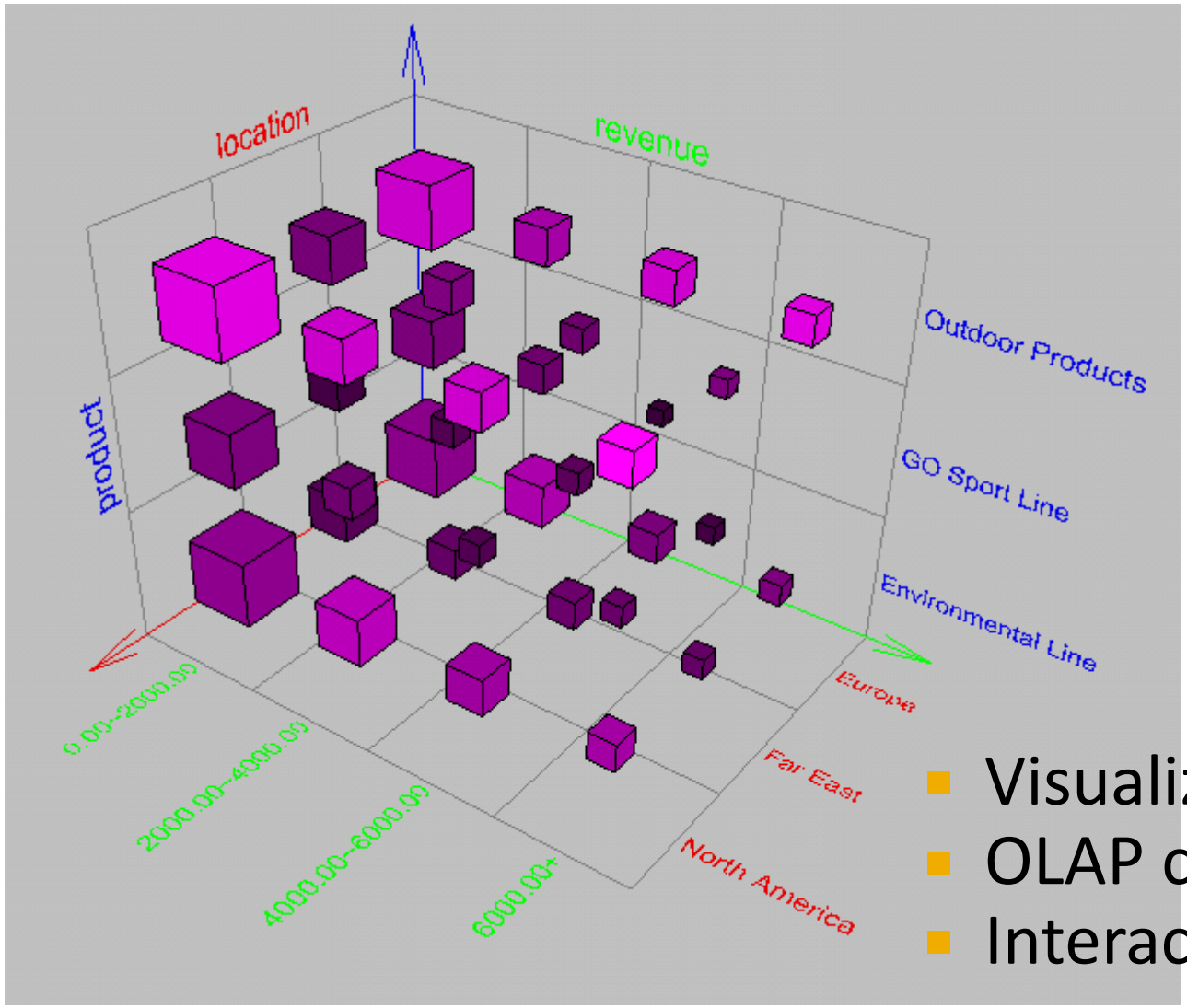


# A Star-Net Query Model




Each circle is called a footprint

# Browsing a Data Cube




- Visualization
- OLAP capabilities
- Interactive manipulation

# Summary

- Data warehousing: A multi-dimensional model of a data warehouse
  - A data cube consists of *dimensions* & *measures*
  - Star schema, snowflake schema, fact constellations
  - OLAP operations: drilling, rolling
- Data Warehouse Architecture, Design, and Usage
  - Multi-tiered architecture
  - Business analysis design framework
  - Information processing, analytical processing, data mining

# Reading List

- Recommended
  - Review Slides!
  - Book: Jiawei Han, Micheline Kamber and Jian Pei, Data Mining - Concepts and Techniques, Morgan Kaufmann, Third Edition, 2011 (or 2nd edition)
    - http://ccs1.hnue.edu.vn/hungtd/DM2012/DataMining_BOOK.pdf
    - Chapters: 3, 4, 5
- Optional
  - (Association Rules) R. Agrawal, T. Imielinski, and A. Swami. Mining association rules between sets of items in large databases. SIGMOD'93