Data Warehousing and OLAP Technology

1. Objectives

- What is a data warehouse?

- Data warehouse design issues.

- General architecture of a data warehouse

- Introduction to Online Analytical Processing (OLAP) technology.

- Data warehousing and data mining relationship.

2. What is Data Warehouse?

2.1. Definitions

- 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 <u>subject-oriented</u>, <u>integrated</u>, <u>time-variant</u>, and <u>nonvolatile</u> collection of data in support of management's decision-making process."—W. H. Inmon
- Operational Data: Data used in day-to-day needs of company.
- Informational Data: Supports other functions such as planning and forecasting.
- Data mining tools often access data warehouses rather than operational data.
- Data warehousing: The process of constructing and using data warehouses.

2.2. 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.

2.3. 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.

2.4. 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".

2.5. Data Warehouse—Non-Volatile

- 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*.

2.6. Data Warehouse vs. Heterogeneous DBMS

- Traditional heterogeneous DB integration:
  - Build wrappers/mediators on top of heterogeneous databases
  - Query driven approach
    - 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

2.7. 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

2.8. 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

2.9. Why 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, and 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.

3. Multidimensional Data Model

3.1. Definitions

- A data warehouse is based on a multidimensional data model which views data in the form of a data cube.

- This is not a 3-dimensional cube: it is n-dimensional cube.

- Dimensions of the cube are the equivalent of entities in a database, e.g., how the organization wants to keep records.

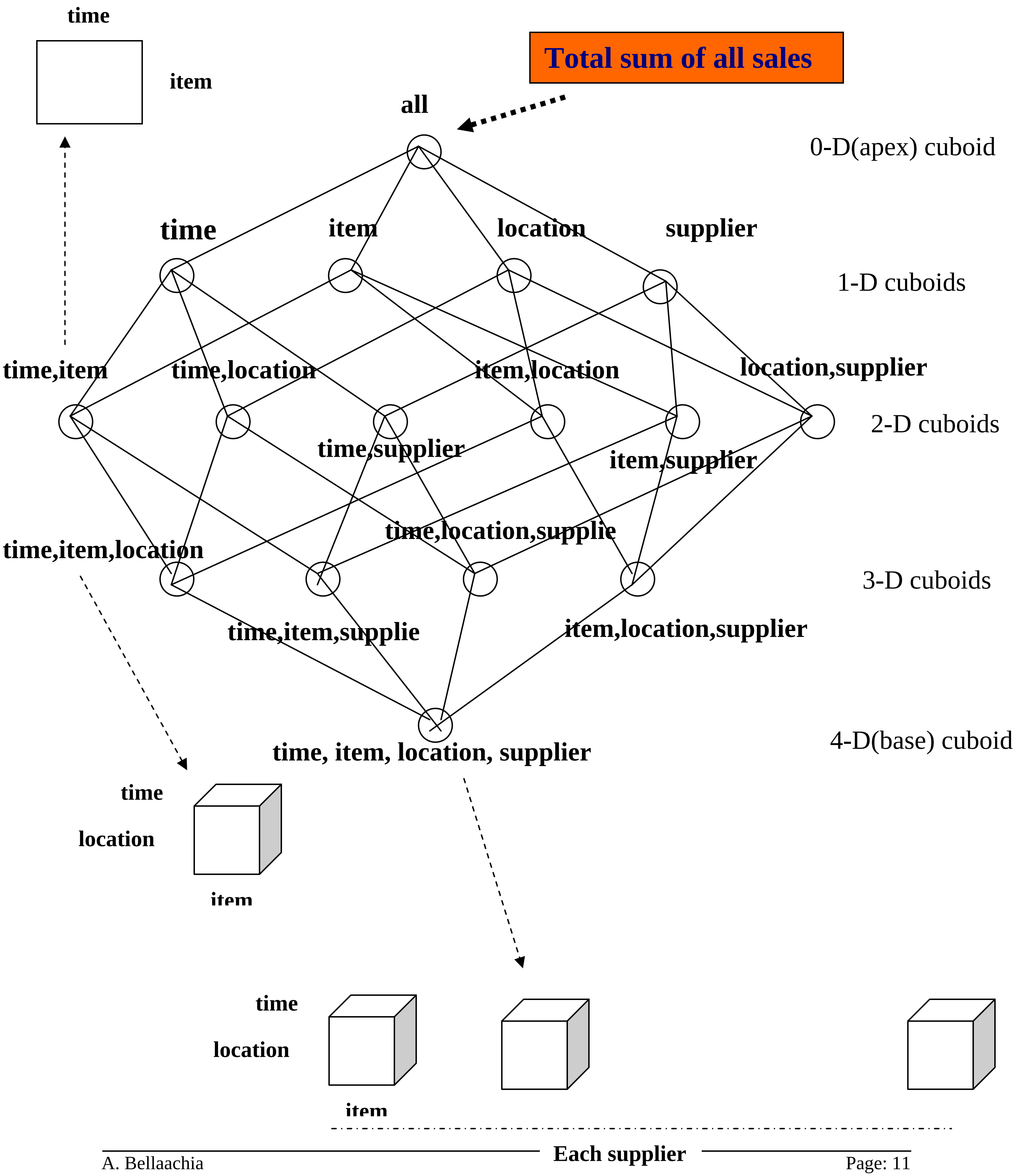
- Examples:
    - Product
    - Dates
    - Locations

- 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.

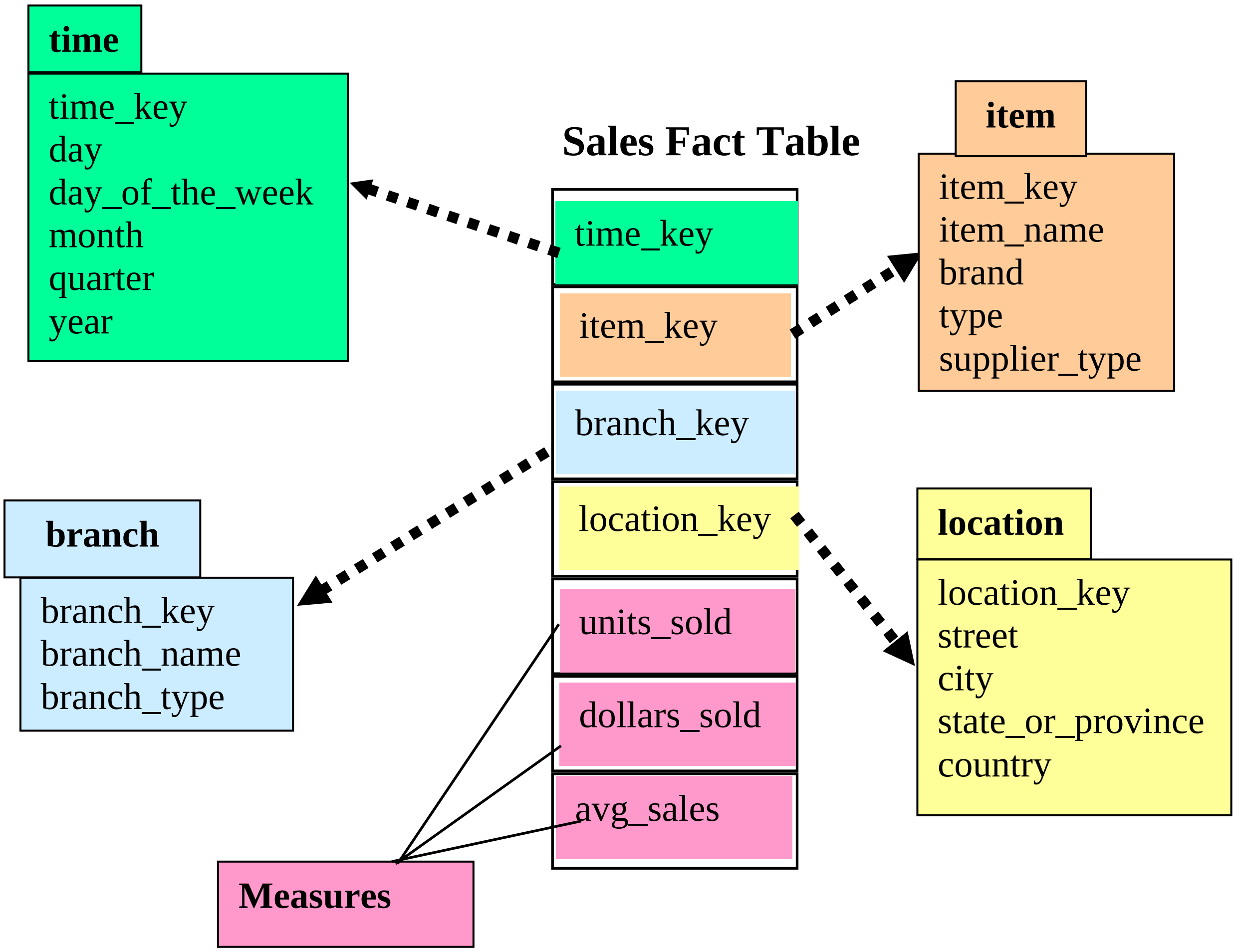
- Cube: A lattice of cuboids



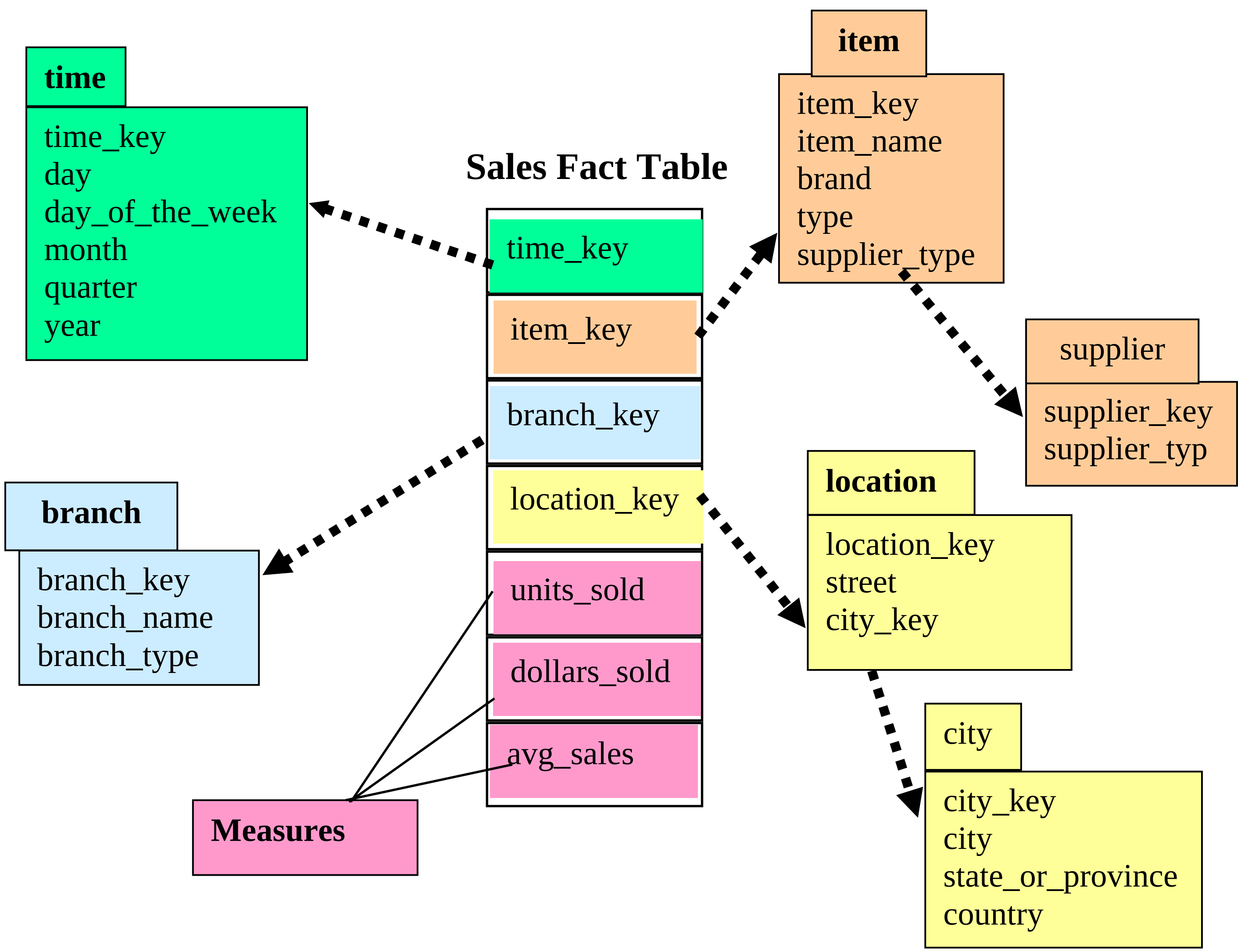
4. Conceptual Modeling of Data Warehousing

- 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

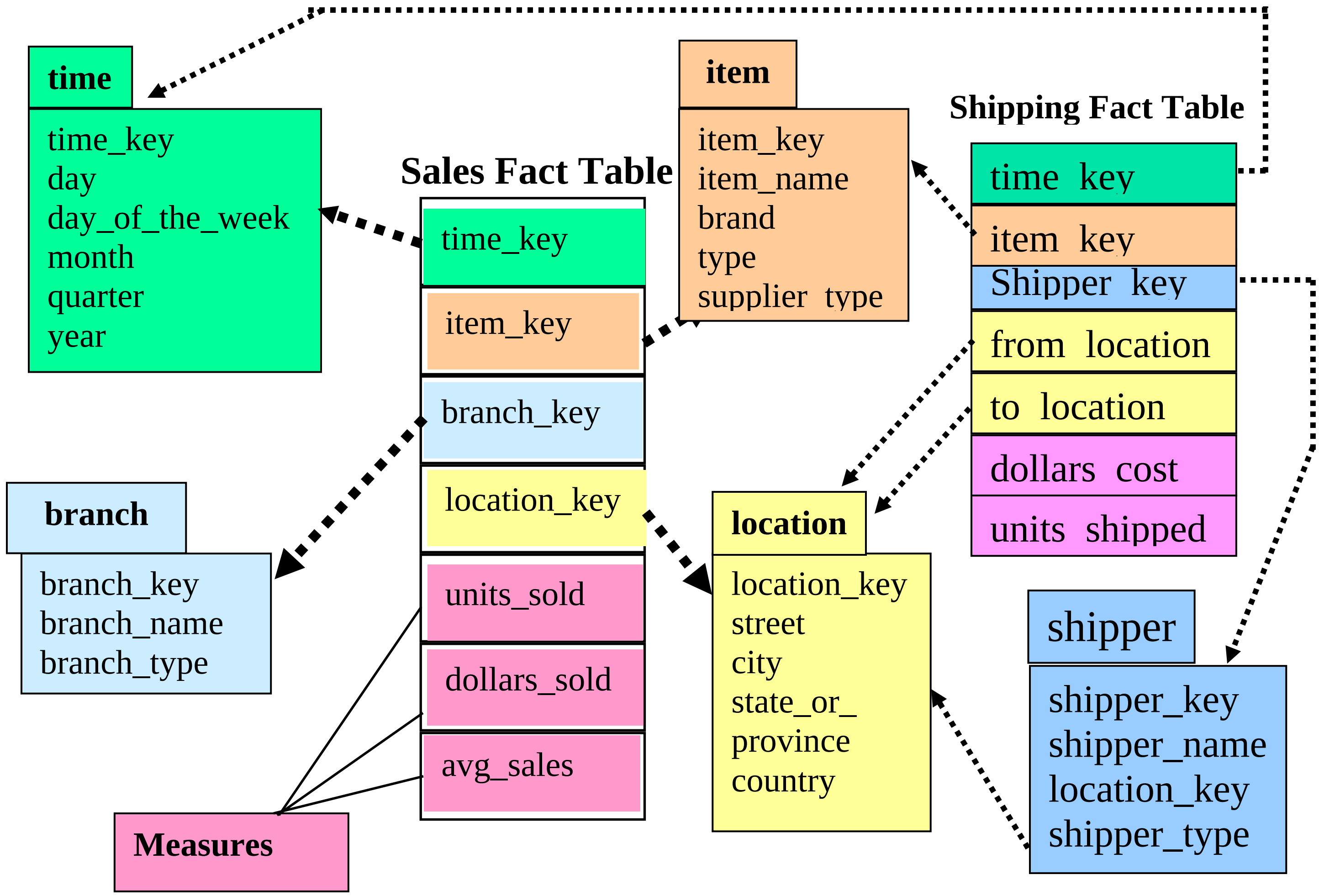
4.1. Star Schema



4.2. Snowflake Schema



4.3. Fact Constellation



5. A Data Mining Query Language: DMQL

5.1. Definitions and syntax

- Similar to RDBMS, we need a DDL (data definition language) to define the tables in the conceptual model.

- Cube Definition (Fact Table)

    - **Syntax:**
      define cube <cube_name> [<dimension_list>]:
      <measure_list>

    - **Example**
      define cube sales_star [time, item, branch, location]:
      dollars_sold = sum(sales_in_dollars)**,**
      avg_sales = avg(sales_in_dollars)**,**
      units_sold = count(*)

- Dimension Definition (Dimension Table)

    - Syntax:
      define dimension <dimension_name>
      as (<attribute_or_subdimension_list>)

    - Example:
      define dimension item
      as (item_key, item_name, brand, type,
      supplier_type)

- Special Case (Shared Dimension Tables)

  - First time as “cube definition”

  - Syntax:
    define dimension <dimension_name>
    as <dimension_name_first_time>
    in cube <cube_name_first_time>

  - Example:

    define dimension item **as** item **in cube** sales

5.2. Defining a Star Schema in DMQL

define cube sales_star [time, item, branch, location]:
dollars_sold = sum(sales_in_dollars),
avg_sales = avg(sales_in_dollars),
units_sold = count(*)

define dimension time **as** (time_key, day, day_of_week, month, quarter, year)

define dimension item **as** (item_key, item_name, brand, type, supplier_type)

define dimension branch **as** (branch_key, branch_name, branch_type)

define dimension location **as** (location_key, street, city, province_or_state, country)

5.3. Defining a Snowflake Schema in DMQL

define cube sales_snowflake [time, item, branch, location]:
dollars_sold = sum(sales_in_dollars),
avg_sales = avg(sales_in_dollars),
units_sold = count(*)

define dimension time **as** (
time_key,
day,
day_of_week,
month,
quarter,
year
)

define dimension item **as** (
item_key,
item_name,
brand, type,
supplier(supplier_key, supplier_type)
)

define dimension branch **as** (branch_key, branch_name, branch_type)

define dimension location **as** (
location_key,
street,
city(city_key, province_or_state, country)
)

5.4. Defining a Fact Constellation in DMQL

define cube sales [time, item, branch, location]:
dollars_sold = sum(sales_in_dollars),
avg_sales = avg(sales_in_dollars),
units_sold = count(*)

define dimension time
as (time_key, day, day_of_week, month, quarter, year)

define dimension item
as (item_key, item_name, brand, type, supplier_type)

define dimension branch
as (branch_key, branch_name, branch_type)

define dimension location
as (location_key, street, city, province_or_state, country)

define cube shipping [time, item, shipper, from_location, to_location]:
dollar_cost = sum(cost_in_dollars),
unit_shipped = count(*)

define dimension time
as time
in cube sales

define dimension item
as item
in cube sales

define dimension shipper
as (shipper_key,
shipper_name,
location **as** location **in cube** sales,
shipper_type)

define dimension from_location
as location
in cube sales

define dimension to_location
as location
in cube sales

5.5. Measures: Three Categories

- A data cube function is a numerical function that can be evaluated at each point in the data cube space.

- Given a data point in the data cube space:

  Entry(v1, v2, …, vn)

  where vi is the value corresponding to dimension di.

  We need to apply the aggregate measures to the dimonsion values v1, v2, …, vn

- **<u>Distributive</u>**:

  - 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.

  - Example: count(), sum(), min(), max().

- **<u>Algebraic</u>**:

  - Use distributive aggregate functions.

  - 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.

- Example: 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().

5.6. How to compute data cube measures?

- How do evaluate the dollars_sold and unit_sold in the star schema of the previous example?

- Assume that the relation database schema corresponding to our example is the following:

  time (time_key, day, day_of_week, month, quarter, year)
  item (item_key, item_name, brand, type, supplier(supplier_key, supplier_type))
  branch (branch_key, branch_name, branch_type)
  location (location_key, street, city, province_or_state, country)
  sales (time_key, item_key, branch_key, location_key, number_of_unit_sold, price)

- Let us then compute the two measures we have in our data cube: dollars_sold and units_sold

```
select s.time_key, s.item_key, s.branch_key,
          s.location_key, sum(s.number_of_units_sold*s.price),
         sum(s.number_of_units_sold)
from time t, item i, branch b, location l, sales s
where s.time_key = t.time_key
          and s.item_key = i.item_key
          and s.branch_key = b.branch_key
          and s.location_key = l.location_key
group by   s.time_key, s.item_key, s.branch_key,
                 s.location_key
```

- Relationship between “data cube” and “group by”?

    - The above query corresponds to the base cuboid.

    - By changing the group by clause in our query, we may generate other cuboids.

    - What is query for the 0-D cuboid or apex?

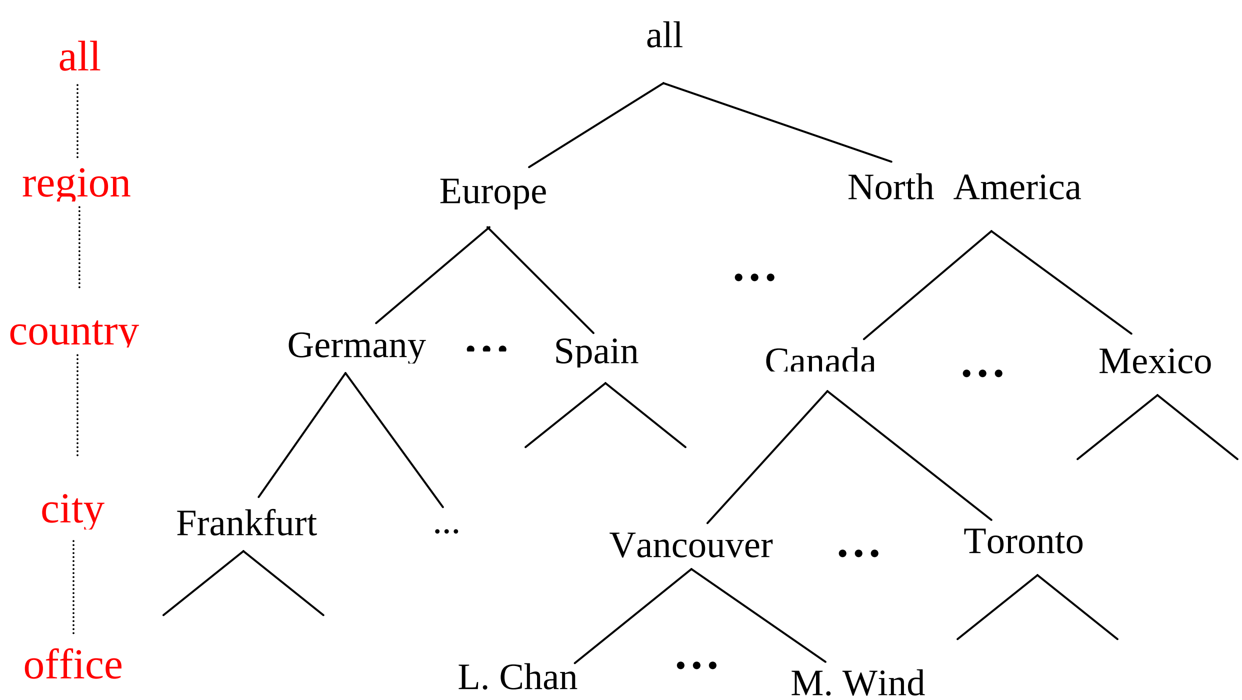
6. A Concept Hierarchy

- A concept hierarchy is an order relation between a set of attributes of a concept or dimension.

- It can be manually (users or experts) or automatically generated (statistical analysis).

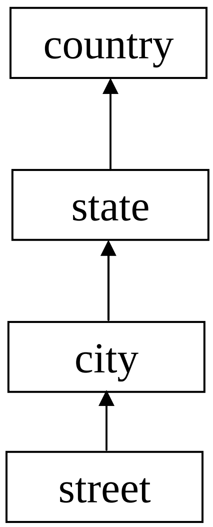
- Multidimensional data is usually organized into dimension and each dimension is further defined into a lower level of abstractions defined by concept hierarchies.

- Example: Dimension (location)

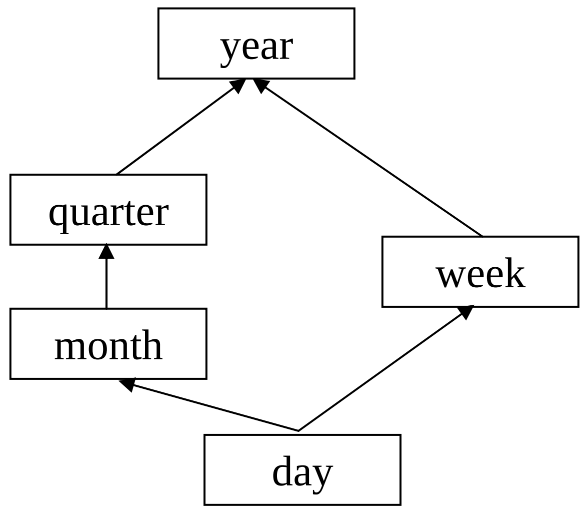


- The order can be either partial or total:

Location dimension: Street <city<state<country
Time dimension: Day < {month<quarter ; week} < year



Total order hierarchy



Partial order hierarchy

- Set-grouping hierarchy:

    - It is a concept hierarchy among groups of values.
    - Example: {1..10} < inexpensive

7. OLAP Operations in a Multidimensional Data

- Sales volume as a function of **product**, **time**, and **region.**

- **Dimensions hierarchical concepts: Product, Location, Time**

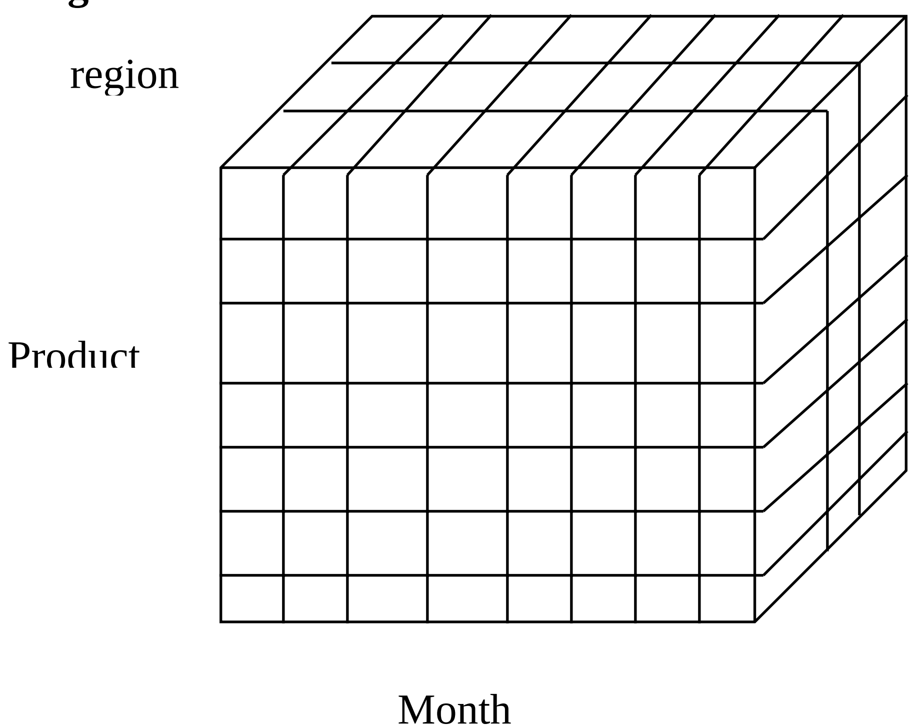
Industry → Category → Product

Region → Country → City → Office

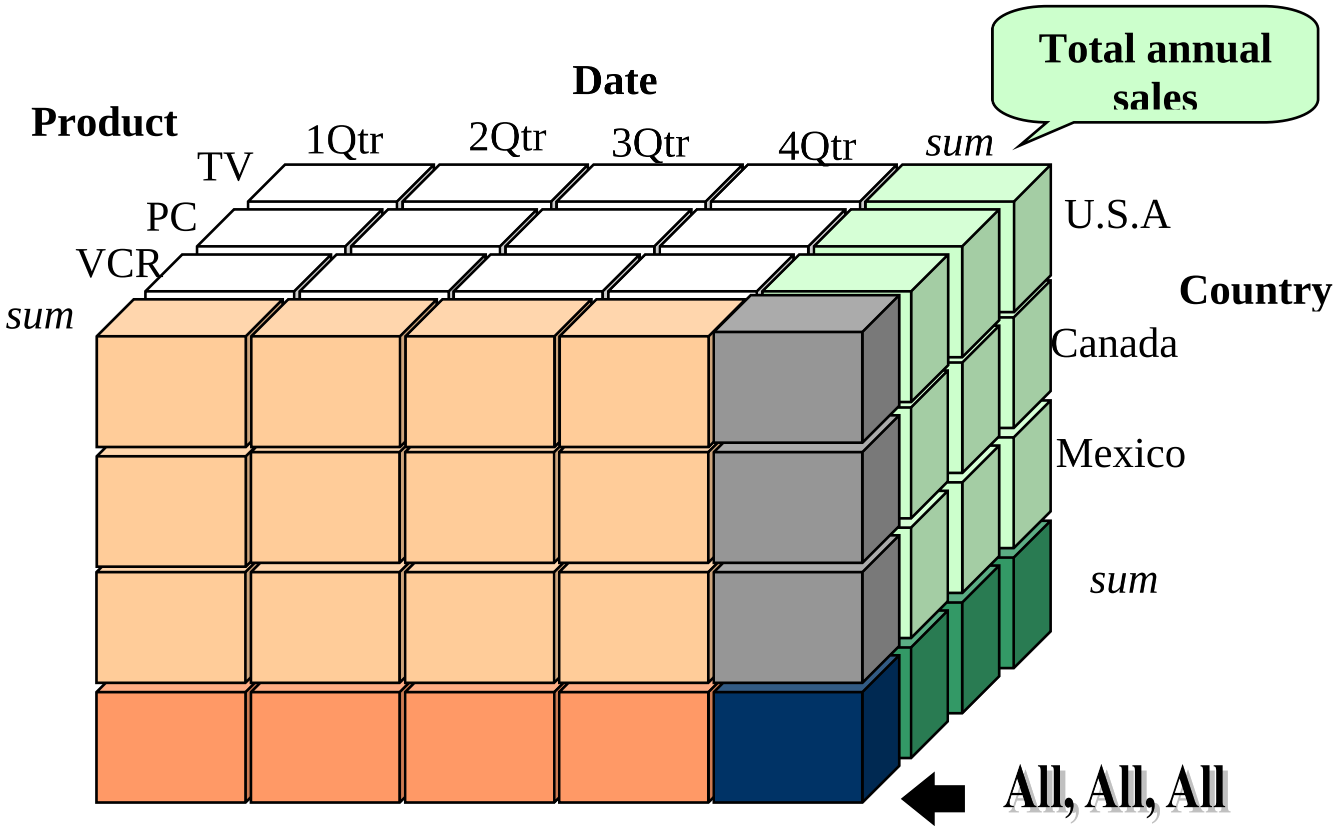
Year → Quarter → Month → Day

Week

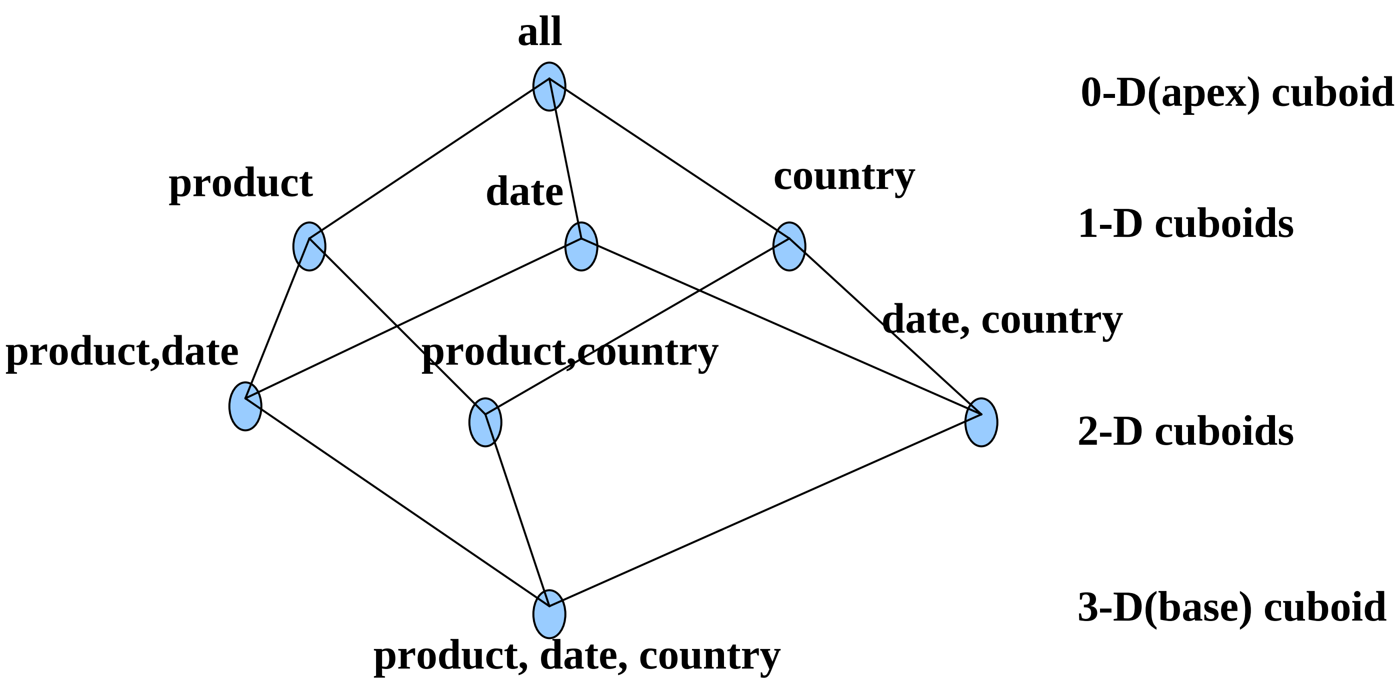
- Sales volume as a function of **product**, **month**, and **region.**



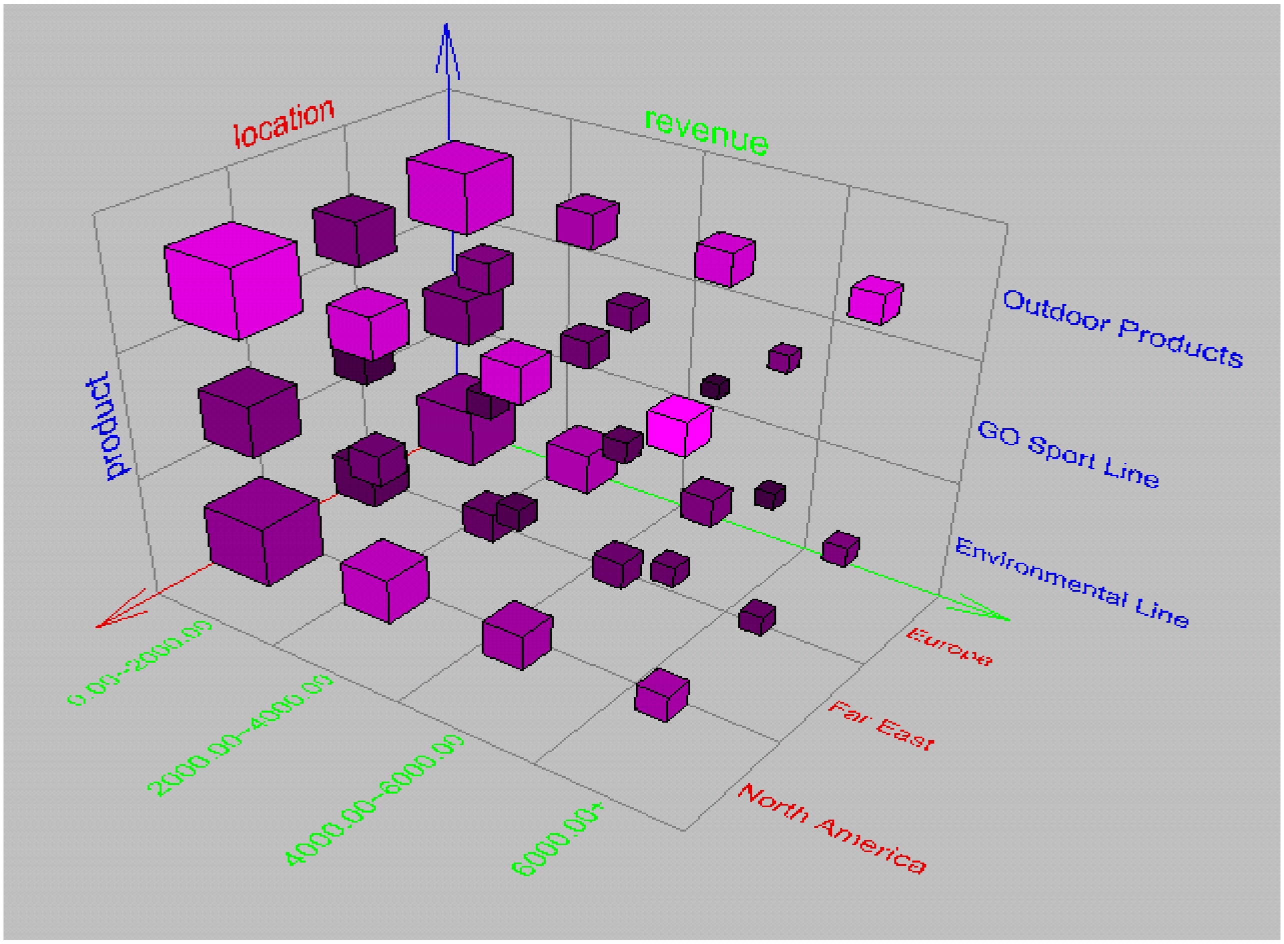
- A Sample data cube:



- Cuboids of the sample cube:



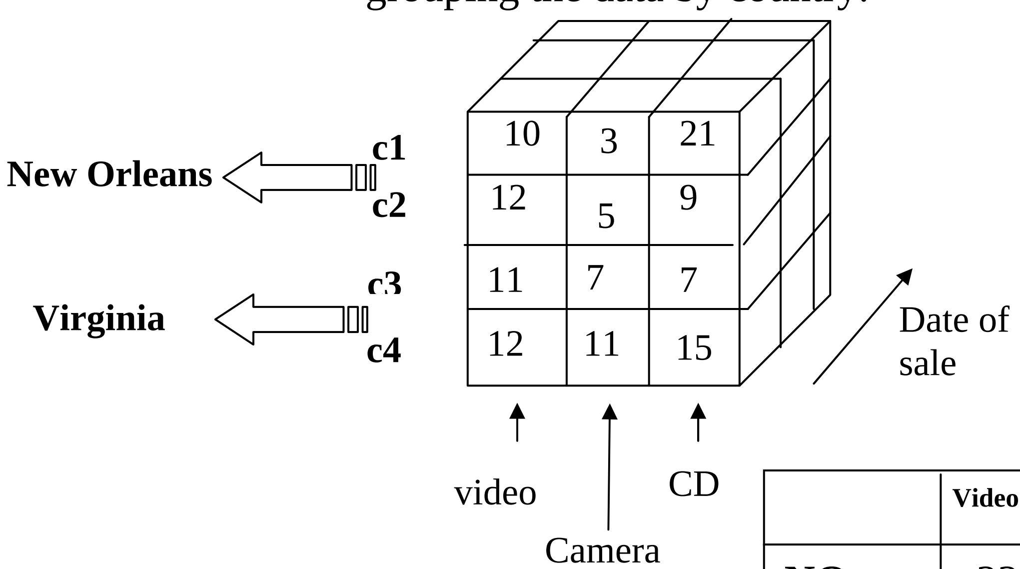
- Querying a data cube



8. OLAP Operations

- Objectives:
  - OLAP is a powerful analysis tool:
    - Forecasting
    - Statistical computations,
    - aggregations,
    - etc.

- Roll up (drill-up): summarize data
  - It is performed by climbing up hierarchy of a dimension or by dimension reduction (reduce the cube by one or more dimensions).
  - The roll up operation in the example is based location (roll up on location) is equivalent to grouping the data by country.



roll up

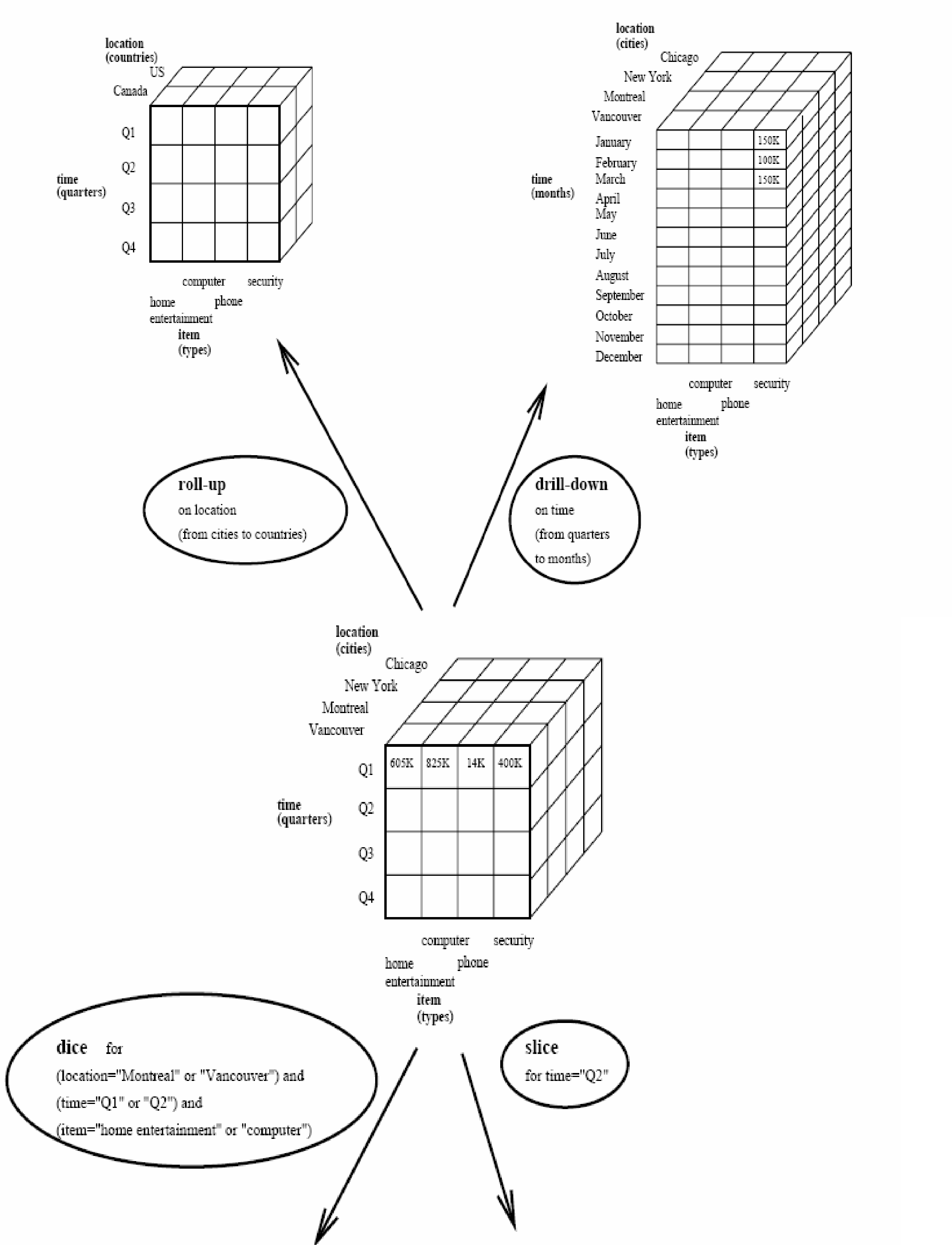
	Video	**Camera**	**CD**
NO	22	8	30
VA	23	18	22

- Drill down (roll down):
    - It is the reverse of roll-up
    - It is performed by stepping down a concept hierarchy for a dimension or introducing new dimensions.

- Slice and Dice:
    - Project and Select operations
    - Check the example.

- Pivot (rotate):
    - Re-orient the cube for an alternative presentation of the data
    - Transform 3D view 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)


location
(countries)
US
Canada
Q1
Q2
time
(quarters)
Q3
Q4
computer
security
home
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entertainment
item
(types)
location
(cities)
Chicago
New York
Montreal
Vancouver
January
February
March
time
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September
October
November
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100K
150K
computer
security
home
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item
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on location
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drill-down
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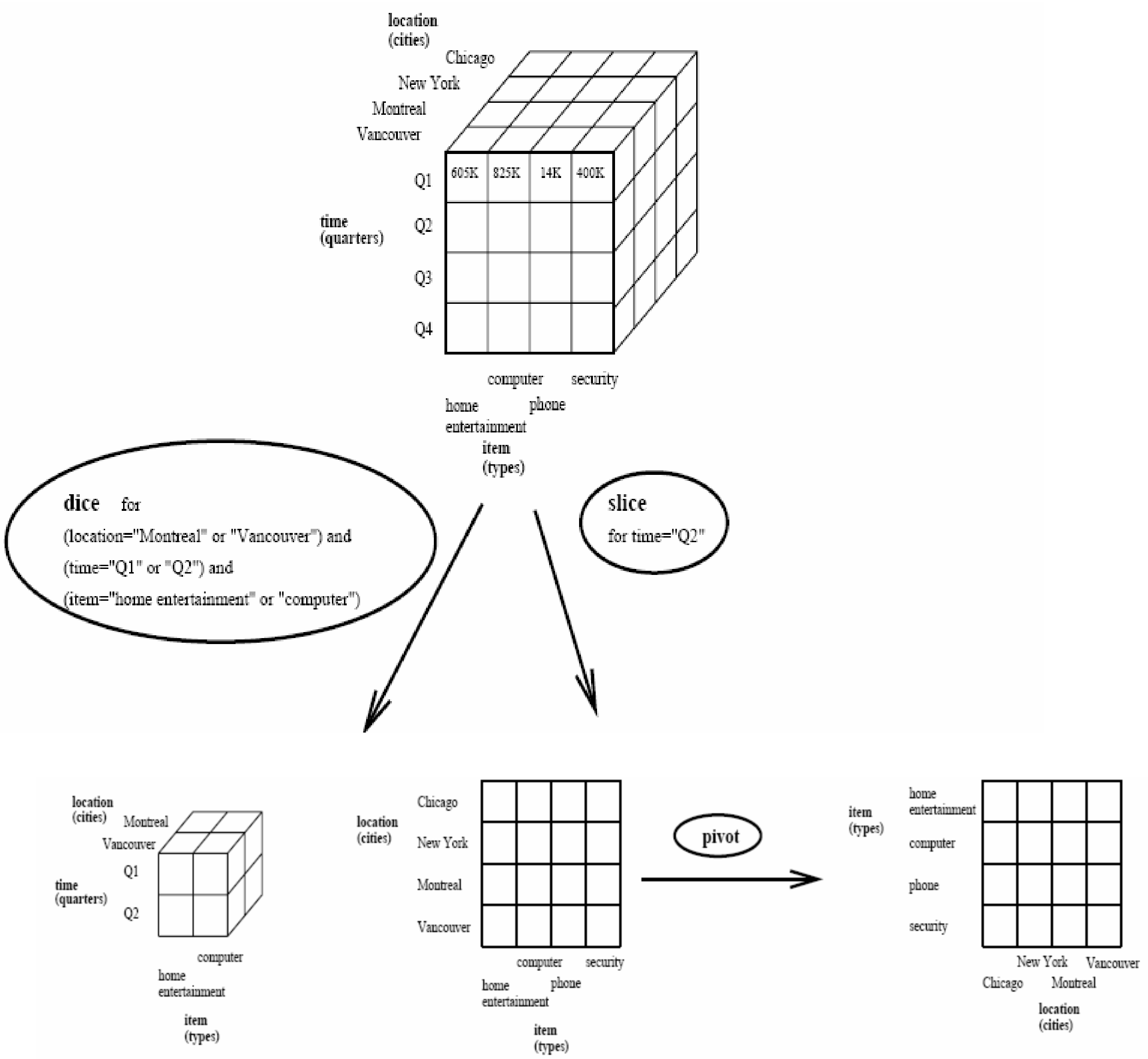
(time="Q1" or "Q2") and
(item="home entertainment" or "computer")
slice
for time="Q2"



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(quarters)
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security
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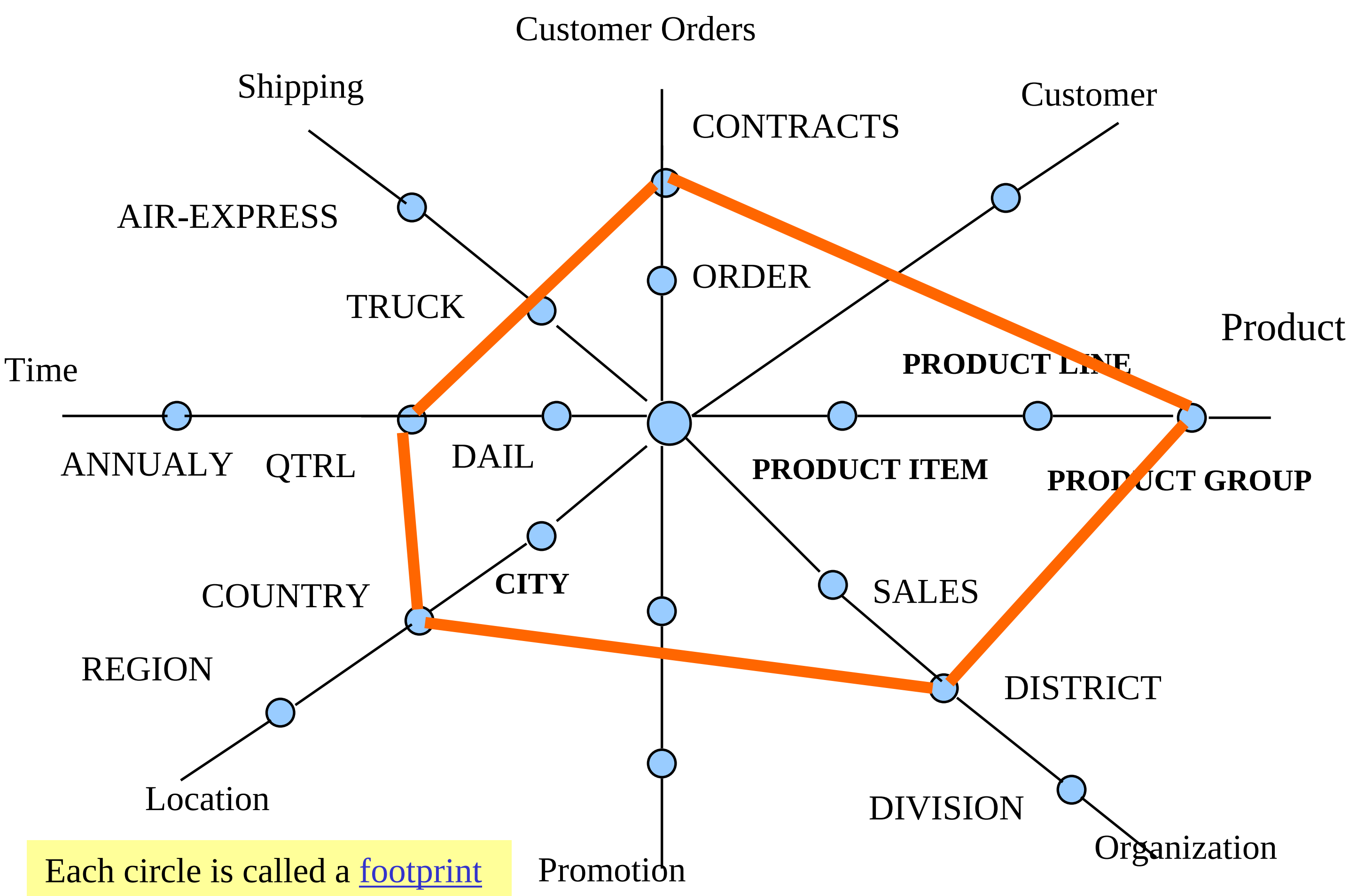
dice for
(location="Montreal" or "Vancouver") and
(time="Q1" or "Q2") and
(item="home entertainment" or "computer")
slice
for time="Q2"
pivot

9. Starnet Query Model for Multidimensional Databases

- Each radial line represents a dimension
- Each abstraction level in a hierarchy concept is called a **footprint**
- Apply OLAP operations.



10. Data warehouse architecture

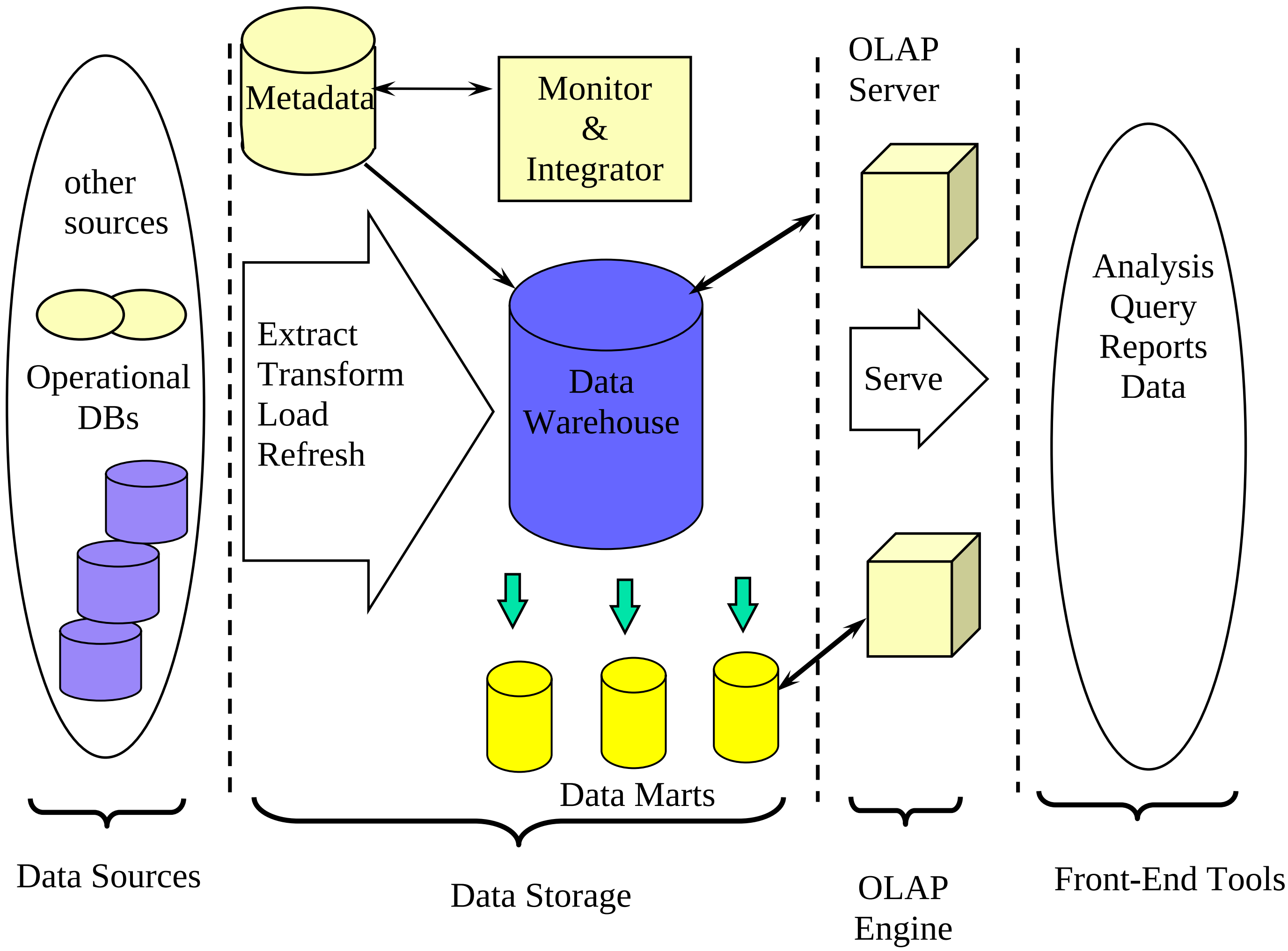
- The design of a successful DW requires the understanding and the analysis of business requirements:
    - Competitive advantage
    - Enhance business productivity
    - Cost reduction

- Four views regarding the design of a data warehouse:
    - Top-down view:
        - allows selection of the relevant information necessary for the data warehouse. It covers the current and future business needs.
    - Data source view:
        - This view exposes the information being captured, stored, and managed by operational systems.
        - Usually modeled by traditional data modeling techniques, e.g., ER model.
    - Data warehouse view:
        - This view consists of fact tables and dimension tables.
    - Business query view:
        - This view sees the perspectives of data in the warehouse from the view of end-user

10.1. DW 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

- Multi-Tiered Architecture



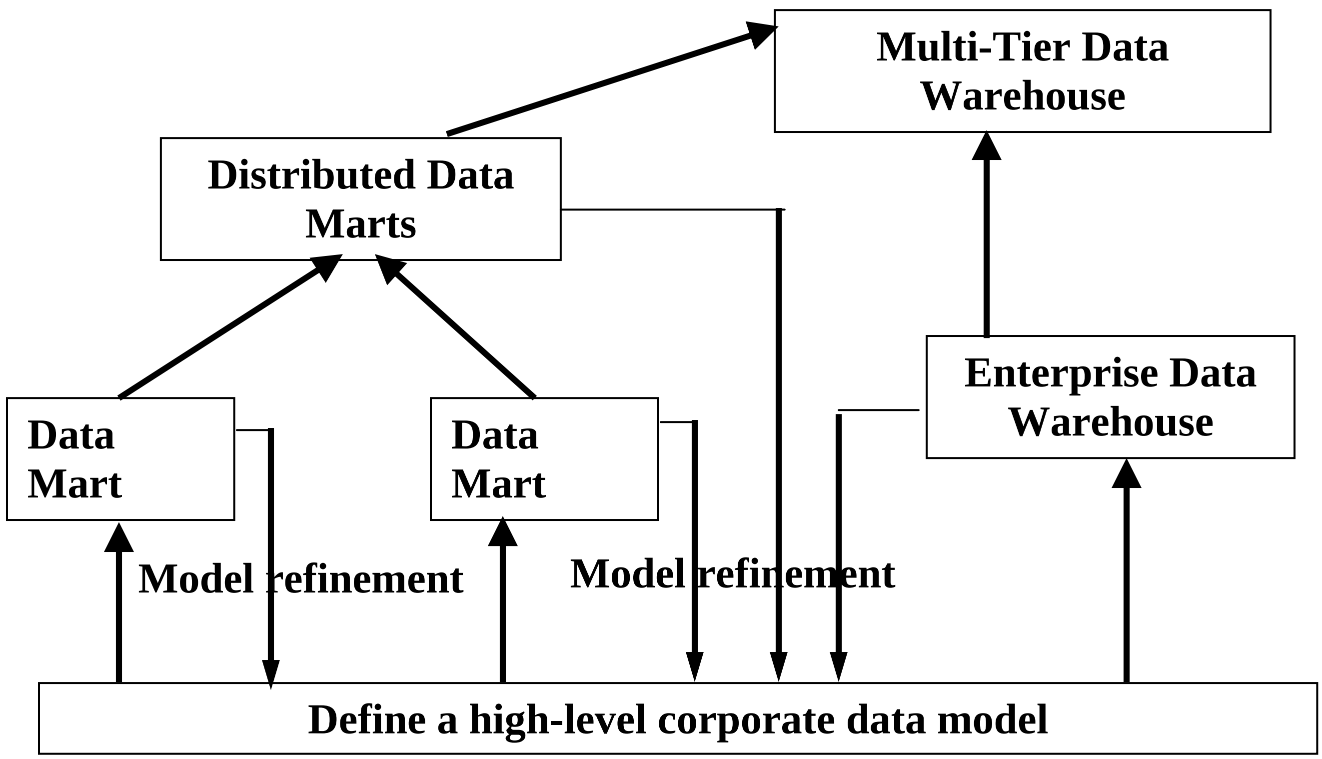
10.2. Three Data Warehouse models

- Enterprise warehouse
    - Collect 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

- A Recommended Approach



- Build the data warehouse incrementally, data marts → data warehouse:
  - Start with a data model
  - Build each data mart in the organization in parallel
  - Integrate the data marts

10.3. OLAP Server Architectures

- Relational OLAP (ROLAP)
    - Use relational or extended-relational DBMS to store and manage warehouse data and OLAP middle ware to support missing pieces
    - Include optimization of DBMS backend, implementation of aggregation navigation logic, and additional tools and services
    - greater scalability

- Multidimensional OLAP (MOLAP)
    - Array-based multidimensional storage engine (sparse matrix techniques)
    - fast indexing to pre-computed summarized data

- Hybrid OLAP (HOLAP)
    - User flexibility, e.g., low level: relational, high-level: array
    - Specialized SQL servers
    - specialized support for SQL queries over star/snowflake schemas

- How data is actually stored in ROLAP and MOLAB?

    - Two methods:
        - Base cuboid data is stored in a `base fact table
        - Aggregate data:
            - Data can be stored in the base fact table (Summary Fact table), or
            - Data can be stored in a separate summary fact tables to store each level of abstraction.

11. Data Warehouse Implementation

- Objectives:

  - **Monitoring:** Sending data from sources
  - **Integrating:** Loading, cleansing,...
  - **Processing:** Efficient cube computation, and query processing in general, indexing, ...

- Cube Computation

  - One approach extends SQL using compute cube operator
  - A cube operator is the n-dimensional generalization of the group-by SQL clause.
  - OLAP needs to compute the cuboid corresponding each input query.
  - Pre-computation: for fast response time, it seems a good idea to pre-compute data for all cuboids or at least a subset of cuboids since the number of cuboids is:

$$\text{number of cuboids} = \begin{cases} 2^n & \textit{If no hierarchy} \\ \displaystyle\prod_{i=1}^{n} (L_i + 1) & \begin{array}{l} \textit{if hierarchy and} \\ L_i \textit{ is number of levels} \\ \textit{associated with } d\text{imension } i \end{array} \end{cases}$$

11.1. Materialization of data cube

- Store in warehouse results useful for common queries
- Pre-compute some cuboids

- This is equivalent to the define new warehouse relations using SQL expressions
- Materialize <u>every</u> (cuboid) (full materialization), <u>none </u>(no materialization), or <u>some (partial materialization)</u>
- Selection of which cuboids to materialize
  - Based on size, sharing, access frequency, etc.
  - Define new warehouse relations using SQL expressions

11.2. Cube Operation

- Cube definition and computation in DMQL

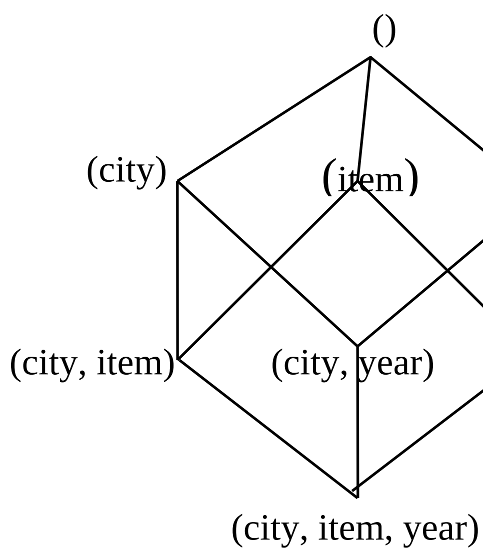
define cube sales[item, city, year]: sum(sales_in_dollars)
compute cube sales

- 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)
()


()
(city)
(item)
(year)
(city, item)
(city, year)
(item, year)
(city, item, year)

11.3. Cube Computation Methods

- ROLAP-based cubing
    - Sorting, hashing, and grouping operations are applied to the dimension attributes in order to reorder and cluster related tuples
    - Grouping is performed on some subaggregates as a “partial grouping step”
    - Aggregates may be computed from previously computed aggregates, rather than from the base fact table
- MOLAP Approach
    - Uses Array-based algorithm
    - The base cuboid is stored as multidimensional array.
    - Read in a number of cells to compute partial cuboids

11.4. Indexing OLAP Data: Bitmap Index

- Approach:
  - 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
- Example:

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

11.5. Indexing OLAP Data: Join Indices

- Join index:

  JI(R-id, S-id)

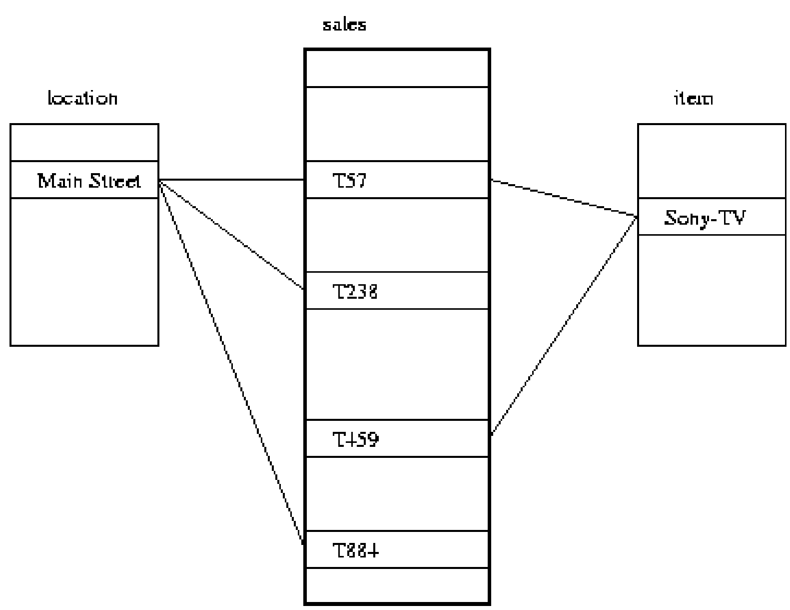
  where R (R-id, …) >< S (S-id, …)

- Traditional indices map the values to a list of record ids

- It materializes relational join in JI file and speeds up relational join — a rather costly operation

- 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



11.6. Efficient Processing OLAP Queries

- Determine which operations should be performed on the available cuboids:
    - transform drill, roll, etc. into corresponding SQL and/or OLAP operations, e.g, dice = selection + projection

- Determine to which materialized cuboid(s) the relevant operations should be applied.

- Exploring indexing structures and compressed vs. dense array structures in MOLAP

11.7. 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.
- Differences among the three tasks

11.8. 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.

- Architecture of OLAM

12. An OLAM Architecture