Data Mining: DWH and OLAP

Chapter 4: Data Warehousing and On-line Analytical Processing

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

Learning Outcomes

- Define the characteristics of a data warehouse
- Design a simple data warehouse schema using fact and dimension tables
- Perform the OLAP operations on a data cube

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*

OLTP vs. OLAP

- OLTP: Online transactional processing
  - DBMS operations
  - Query and transactional processing
- OLAP: Online analytical processing
  - Data warehouse operations
  - Drilling, slicing, dicing, etc.

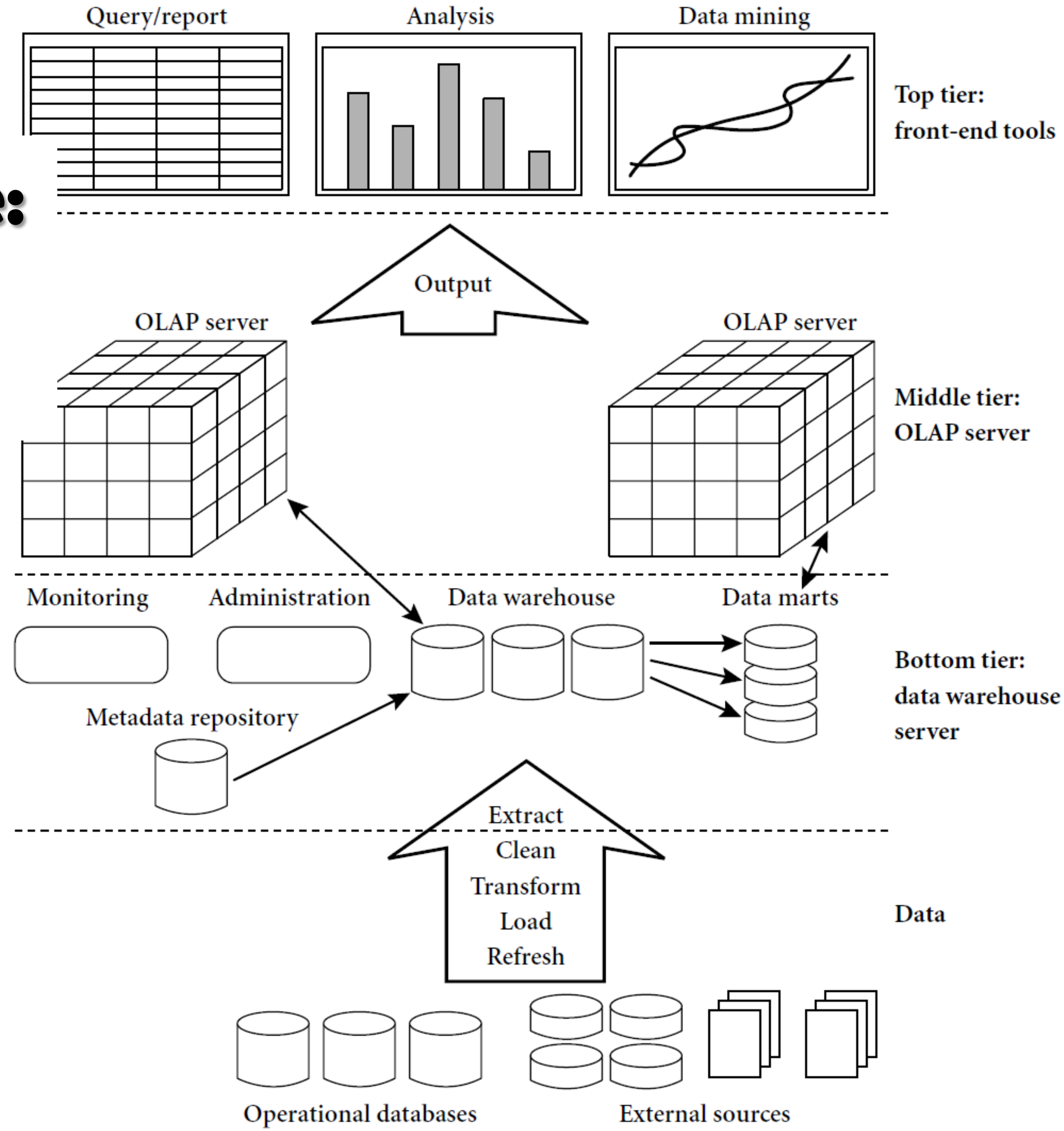
	OLTP	OLAP
users	clerk, IT professional	knowledge worker
function	day to day operations	decision support
DB design	application-oriented	subject-oriented
data	current, up-to-date detailed, flat relational isolated	historical, summarized, multidime integrated, consolidatec
usage	repetitive	ad-hoc
access	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, respc

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

Data Warehouse: A Multi-Tiered Architecture

- Top Tier: Front-End Tools
- Middle Tier: OLAP Server
- Bottom Tier: Data Warehouse Server
- Data



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

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

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

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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

2-D Vs 3-D View

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

	location = "Chicago"				**location** = "New York"				**location** = "Toronto"				**location** = "Vancouver"			
	item				**item**				**item**				**item**			
time	*home ent.*	*comp.*	*phone*	*sec.*	*home ent.*	*comp.*	*phone*	*sec.*	*home ent.*	*comp.*	*phone*	*sec.*	*home ent.*	*comp.*	*phone*	*sec.*
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

3-D View and 3-D Cube

	location = "Chicago"				location = "New York"				location = "Toronto"				location = "Vancouver"			
	item				item				item				item			
time	home ent.	comp.	phone	sec.	home ent.	comp.	phone	sec.	home ent.	comp.	phone	sec.	home ent.	comp.	phone	sec.
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
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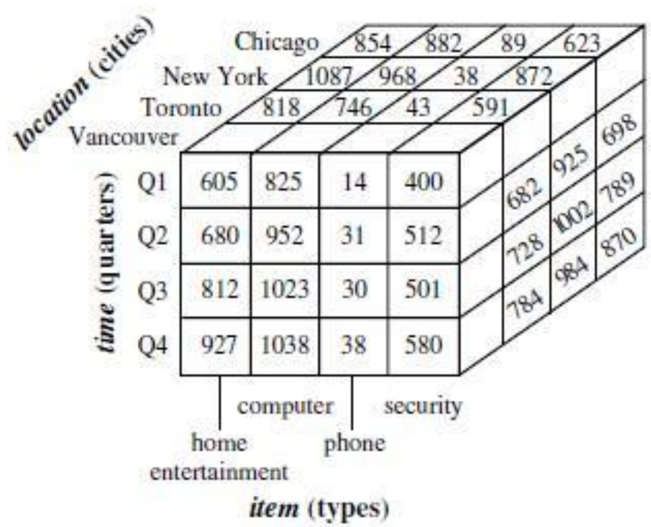
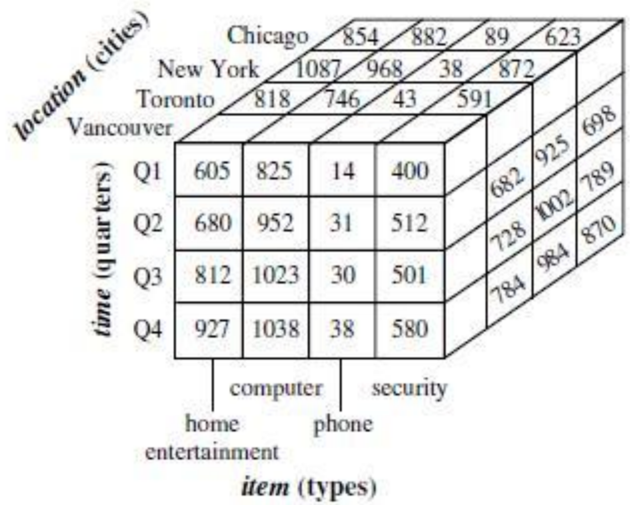
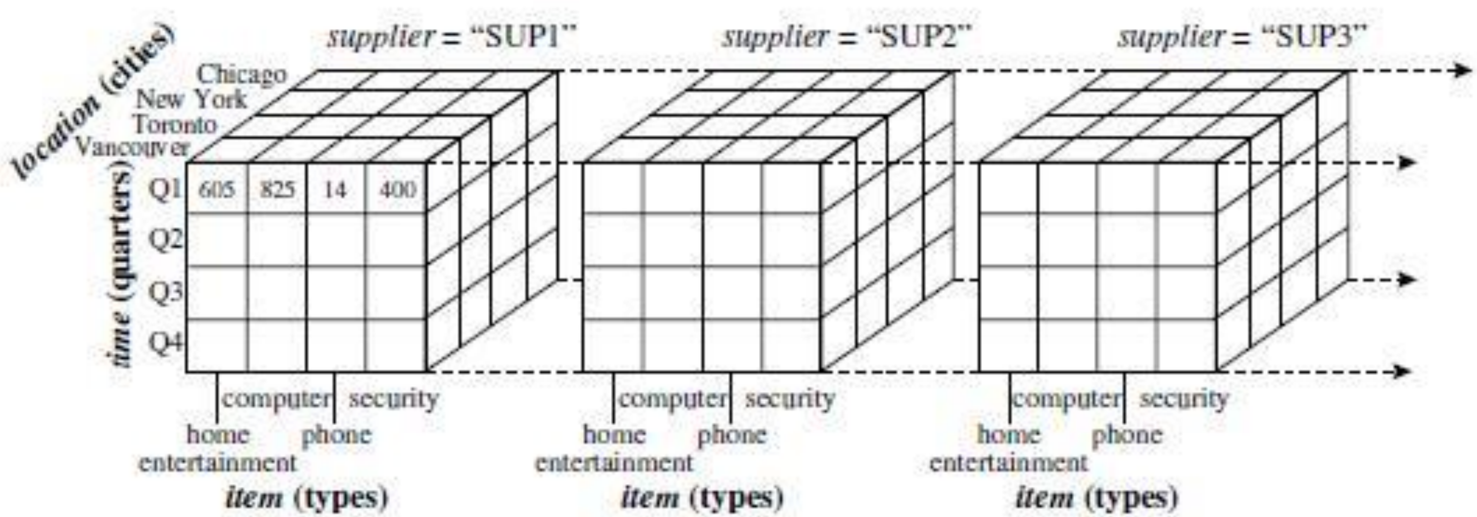


3-D Vs 4-D Cube



location (cities)
Chicago
854
882
89
623
New York
1087
968
38
872
Toronto
818
746
43
591
Vancouver
698
925
682
789
1002
728
870
984
784
time (quarters)
Q1
605
825
14
400
Q2
680
952
31
512
Q3
812
1023
30
501
Q4
927
1038
38
580
computer
security
home entertainment
phone
item (types)



supplier = "SUP1"
supplier = "SUP2"
supplier = "SUP3"
location (cities)
Chicago
New York
Toronto
Vancouver
time (quarters)
Q1
Q2
Q3
Q4
605
825
14
400
computer
security
home entertainment
phone
item (types)
computer
security
home entertainment
phone
item (types)
computer
security
home entertainment
phone
item (types)

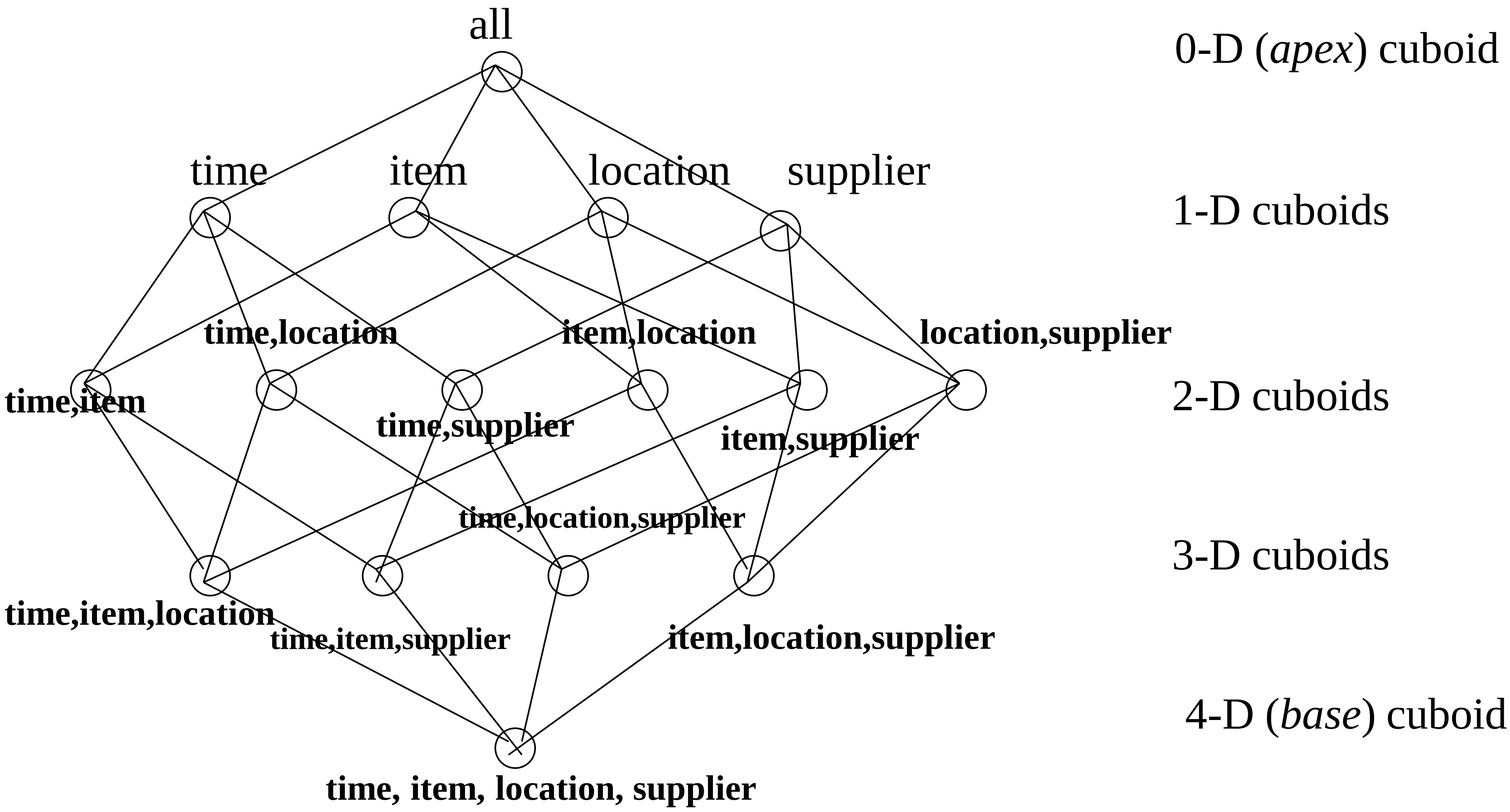
Exercise 1

- Identify the dimensions and facts from the following attributes:
  - Time, Location, Item Type, Supplier, Items Sold, Dollars Sold
- Create a lattice for all the dimensions
- Give an example of apex cuboid query
- Give an example of query on 3 dimensions
- Give an example of n-d cuboid query

Exercise 1

- Identify the dimensions and facts from the following attributes:
  - Time, Location, Item Type, Supplier, Items Sold, Sales amount
  - Dimensions
    - Time, Location, Item Type, Supplier
  - Facts
    - Items sold, Sales amount

Cube: A Lattice of Cuboids (can be used for any fact)



Cuboids and Cubes

- 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.

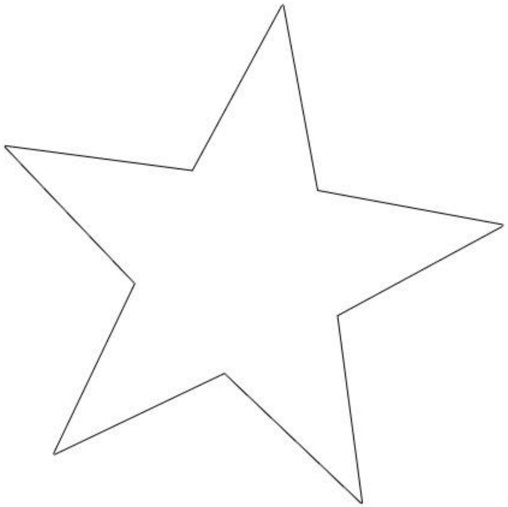
Exercise 1

- Give an example of apex cuboid query
  - There is only one possible query: How many sales/item sold were there for all the time, all the item types, all the locations, and all the suppliers (answer will be just one number which is sum of all the fact numbers)
- Give an example of query on 3 dimensions
  - E.g., for 3 dimension time, location, and item type, the query can be: how many items were sold in Q1, in Chicago, of Phones?
- Give an example of n-d cuboid query
  - It will combine all (4) dimensions e.g.,: how many items were sold in Q3, in New York, of Computers, by Supplier 3?

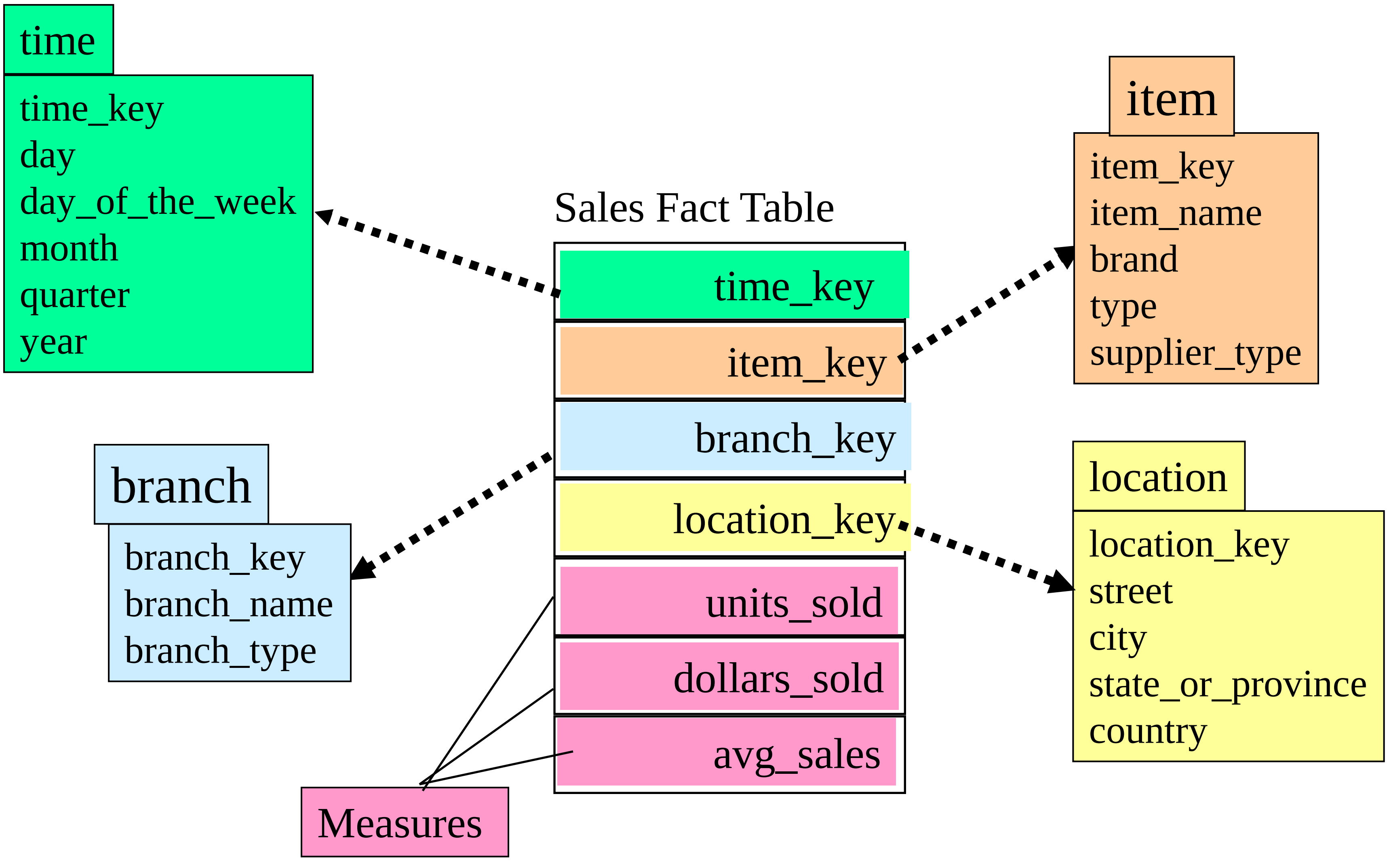
Conceptual Modeling of Data Warehouses

- 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

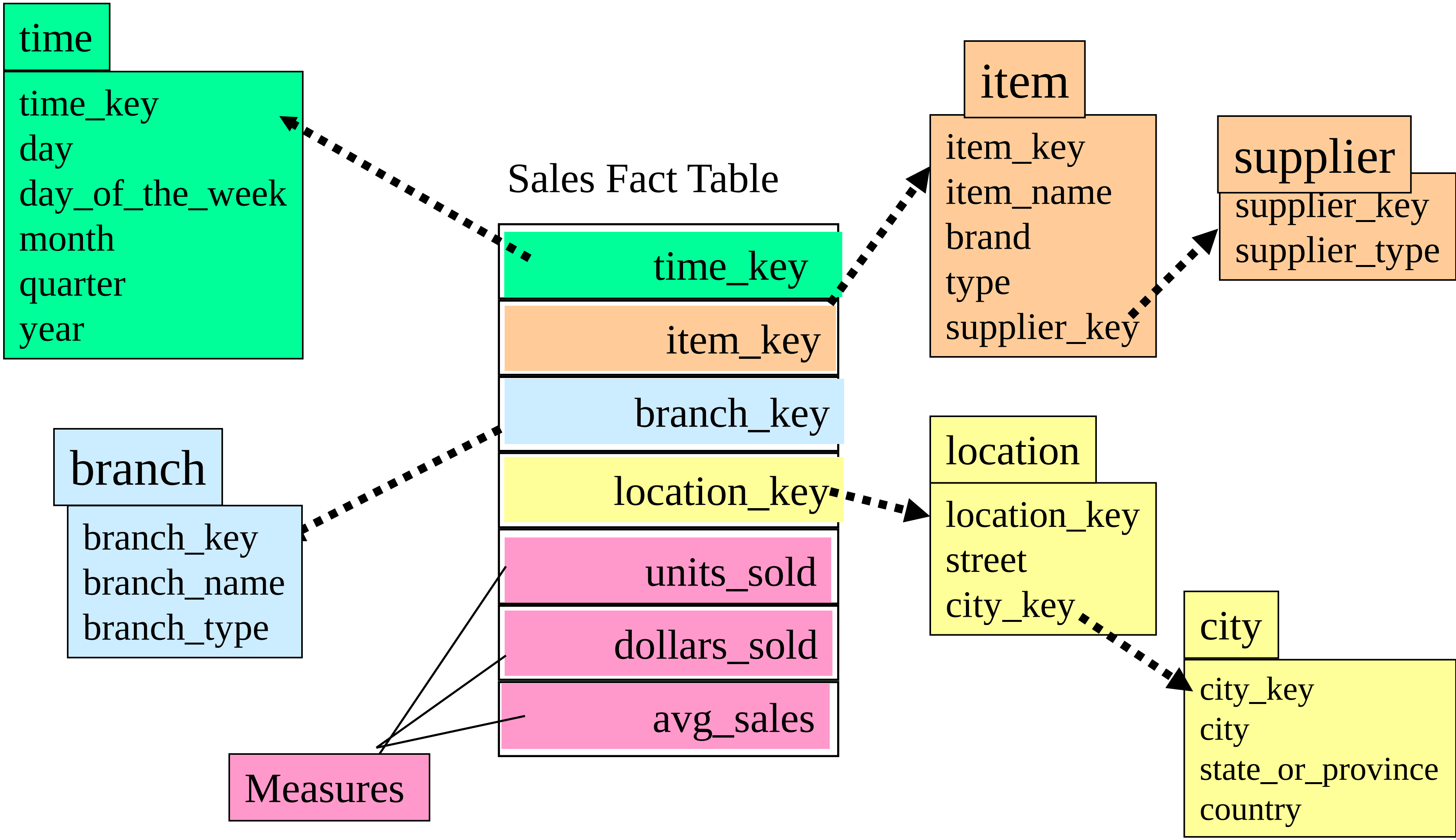
Star, Snowflake and Constellation



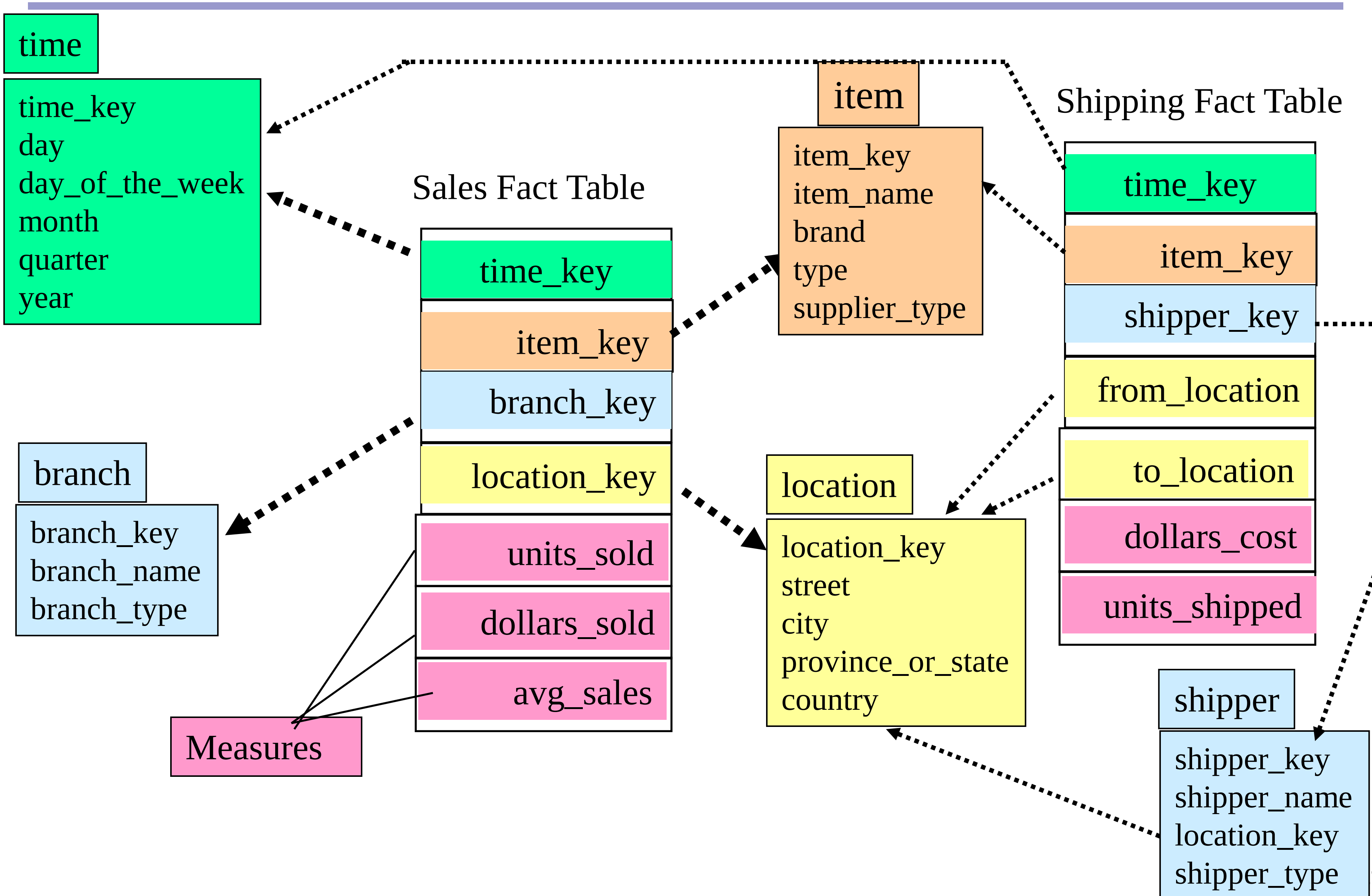
Example of Star Schema



Example of Snowflake Schema



Example of Fact Constellation



Exercise 2

- Create a star schema for weather station with dimensions: time and location and facts: temperature, humidity, air pressure, and precipitation.

Exercise 2

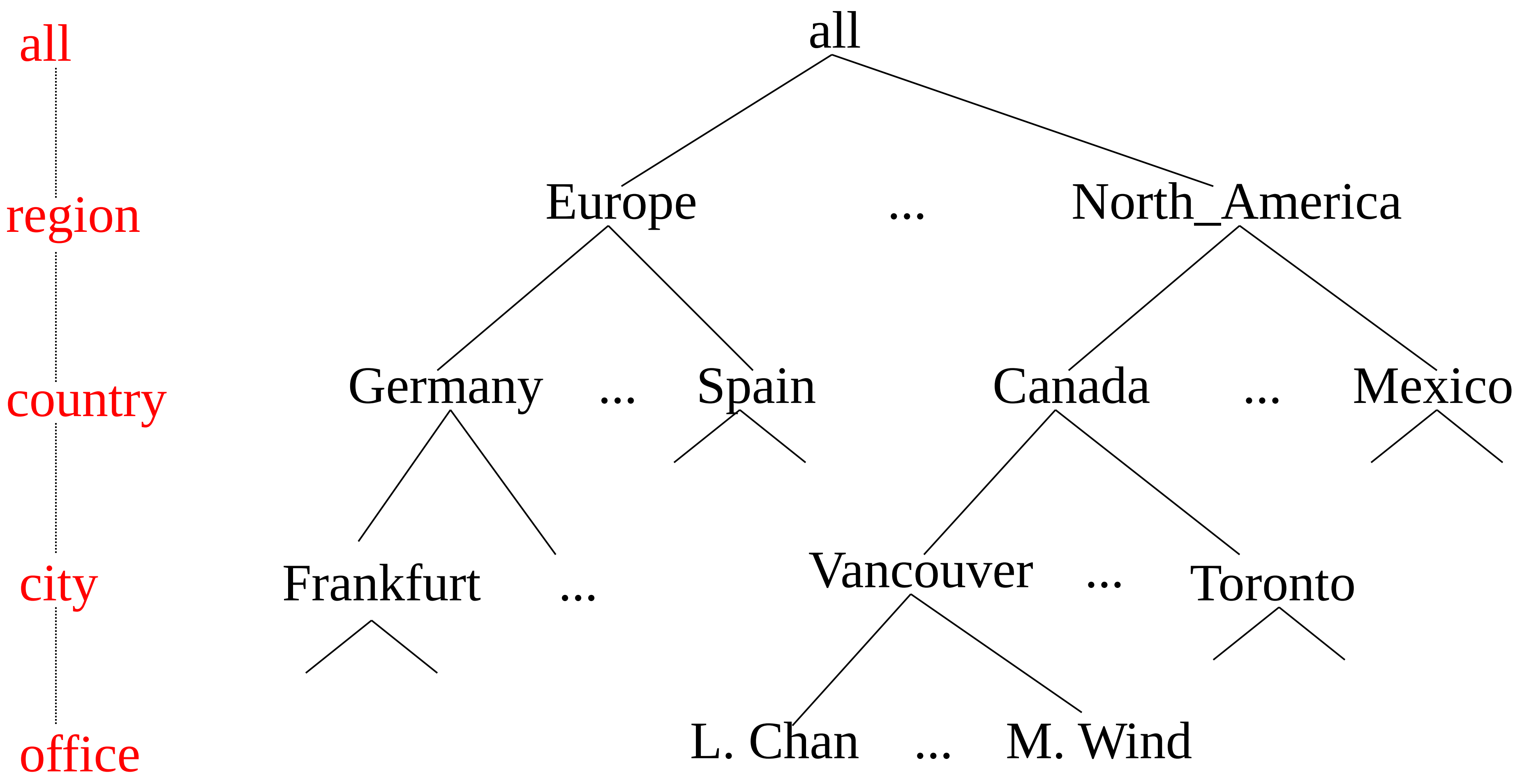
- Create a star schema for weather station with dimensions: time and location and facts: temperature, humidity, air pressure, and precipitation.

Time_id
Hour
Day
Week
Month
Year

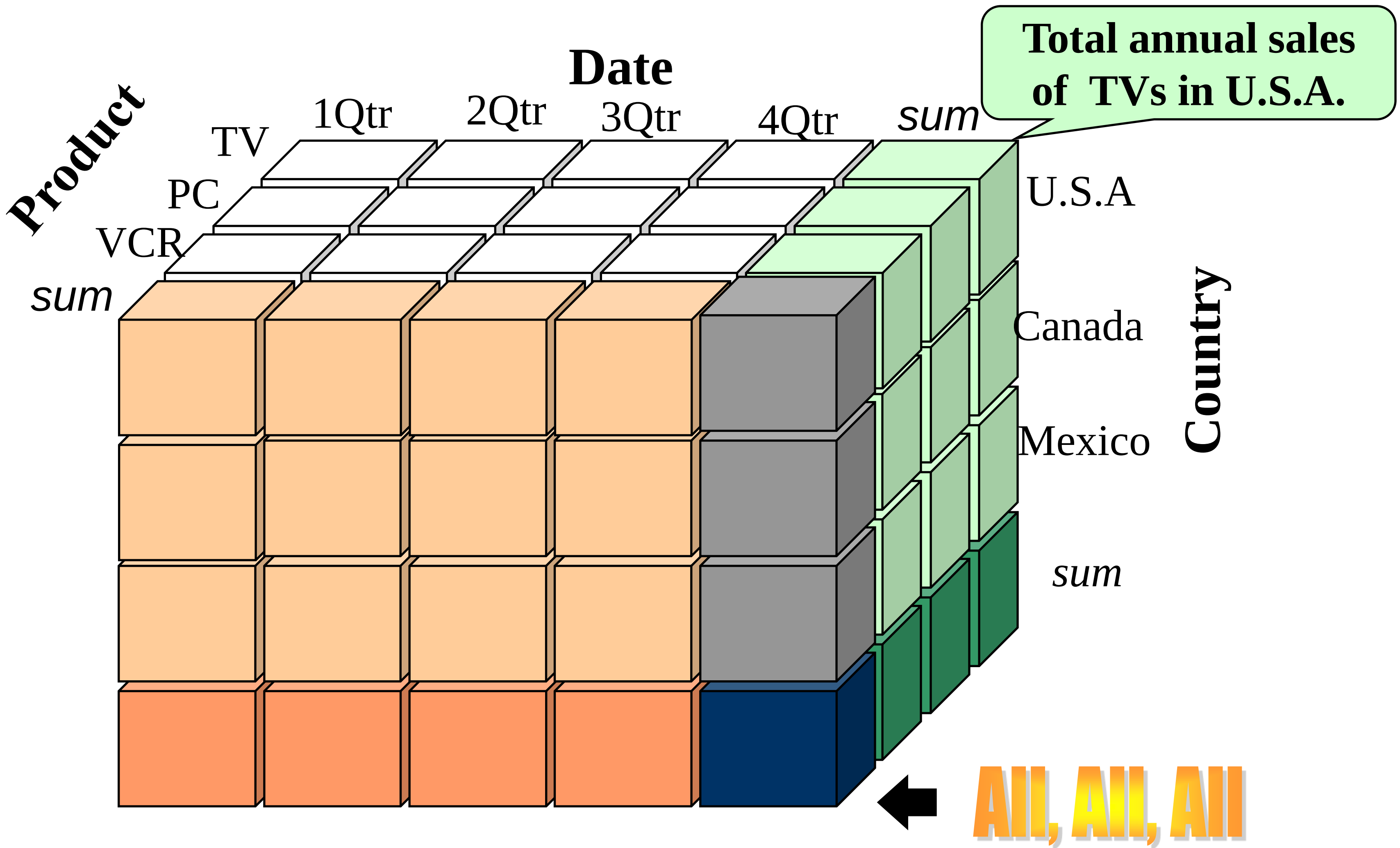
Time_id
Location_id
Average Temperature
Average Humidity
Average Air Pressure
Average Precipitation

Location_id
City
Province Country

A Concept Hierarchy: Dimension (location)

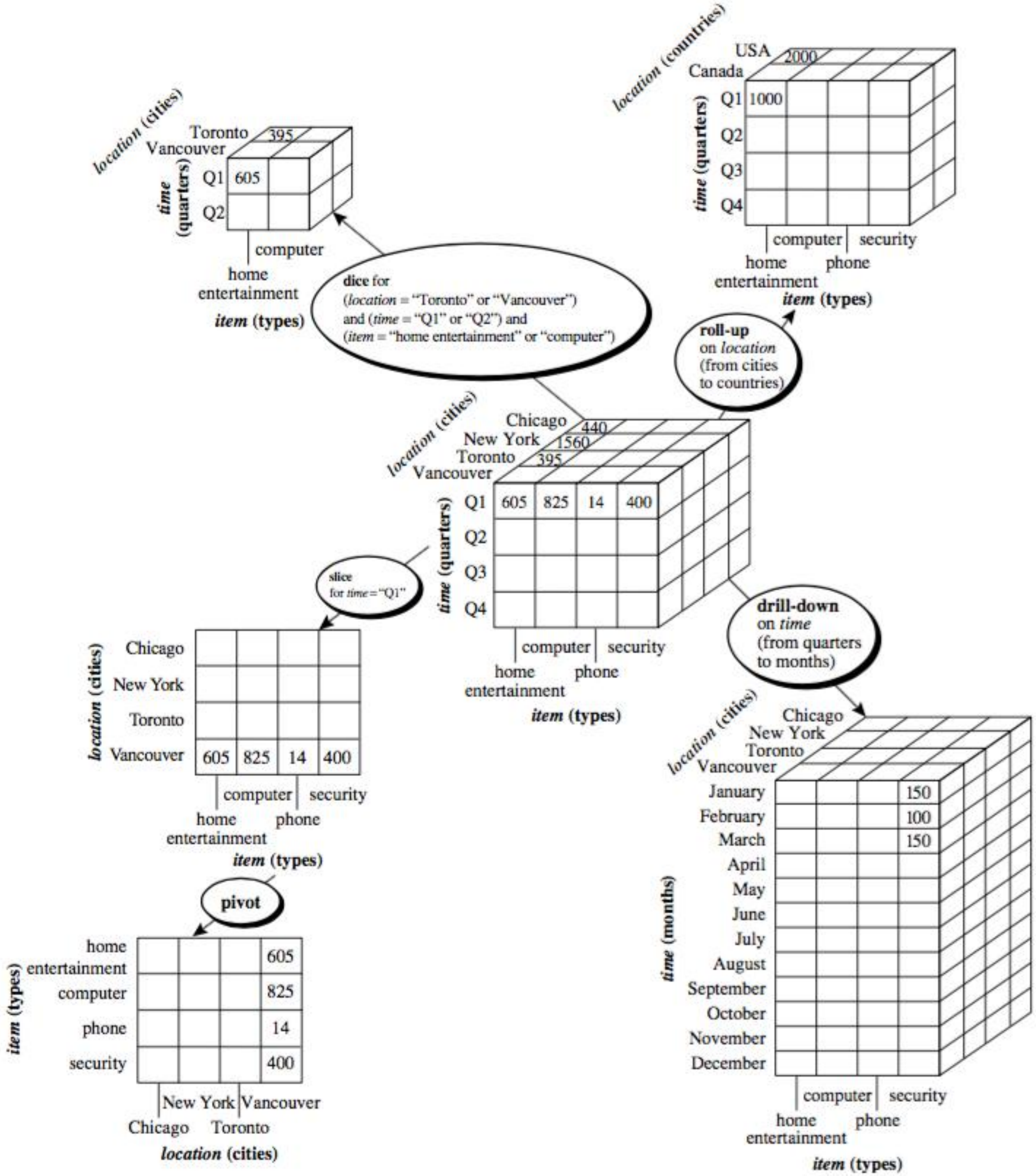


A Sample Data Cube



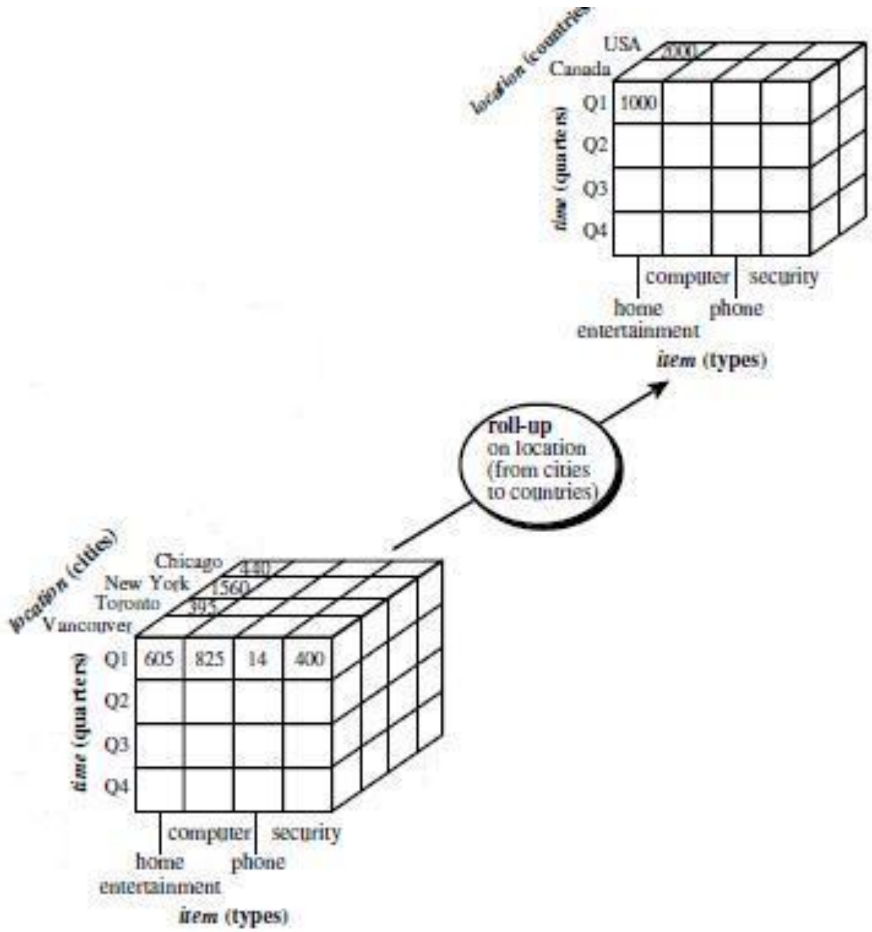
Typical OLAP Operations

- 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)*

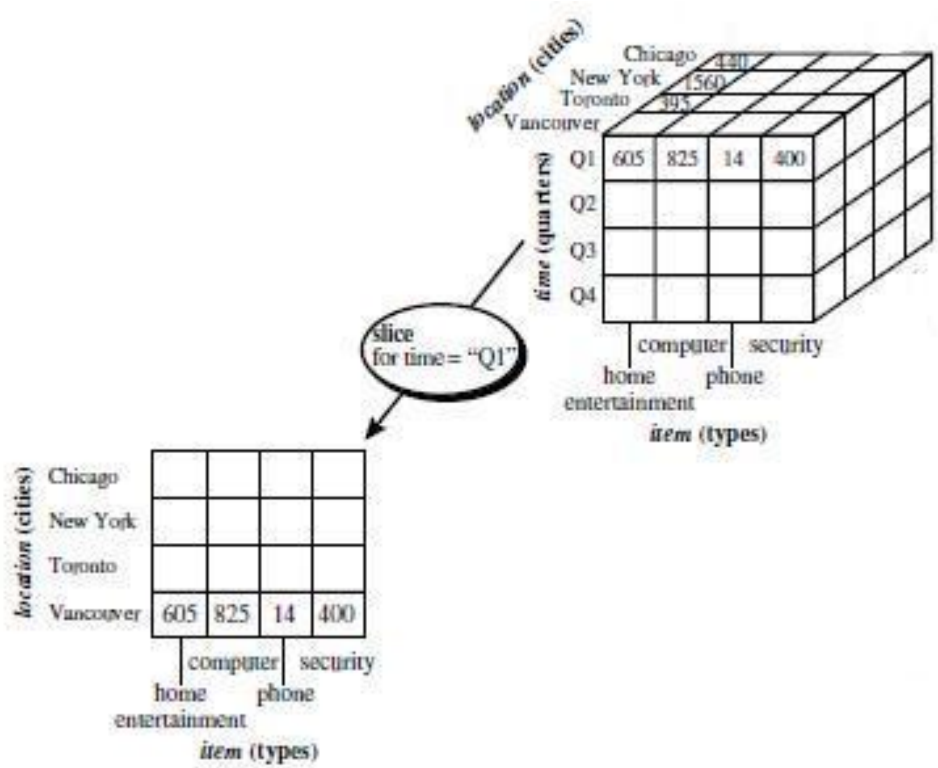


location (countries)
USA
Canada
2000
Q1 1000
Q2
Q3
Q4
time (quarters)
computer
security
home entertainment
phone
item (types)
roll-up on location (from cities to countries)
location (cities)
Toronto
Vancouver
395
Q1 605
Q2
time (quarters)
computer
home entertainment
item (types)
dice for (location = "Toronto" or "Vancouver") and (time = "Q1" or "Q2") and (item = "home entertainment" or "computer")
Chicago
New York
Toronto
Vancouver
440
1560
395
Q1 605 825 14 400
Q2
Q3
Q4
slice for time = "Q1"
drill-down on time (from quarters to months)
location (cities)
Chicago
New York
Toronto
Vancouver 605 825 14 400
pivot
item (types)
home entertainment 605
computer 825
phone 14
security 400
Chicago
New York
Toronto
Vancouver
location (cities)
January 150
February 100
March 150
April
May
June
July
August
September
October
November
December
time (months)

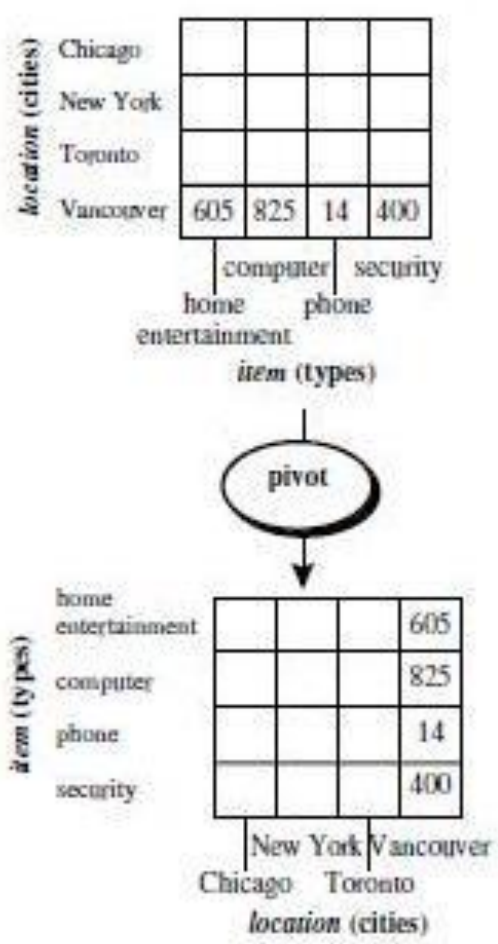
Roll-up and Drill-down



Slice and Dice

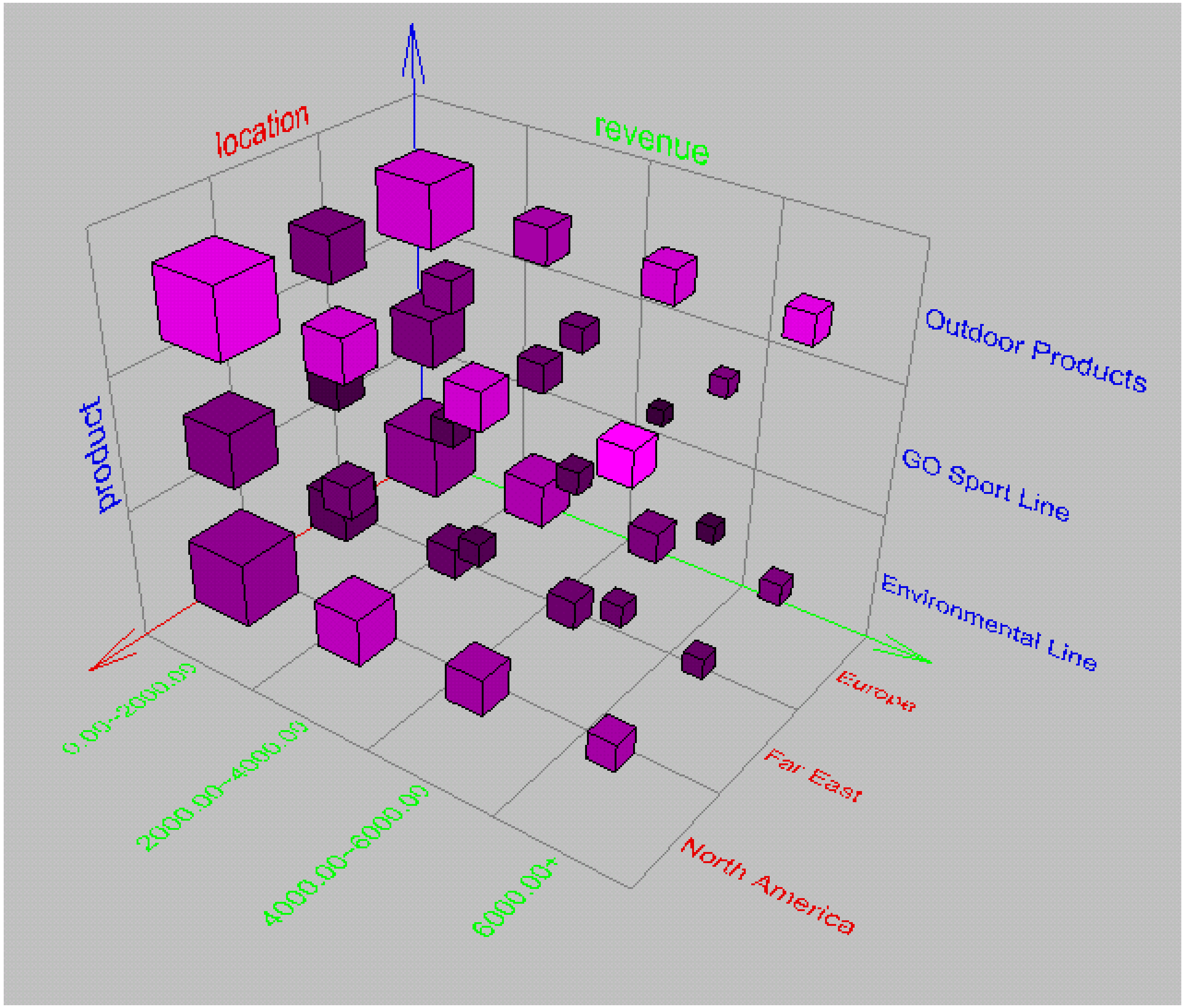


Pivot



location (cities)
Chicago
New York
Toronto
Vancouver
605
825
14
400
computer
security
home entertainment
phone
item (types)
pivot
home entertainment
computer
phone
security
item (types)
605
825
14
400
New York
Vancouver
Chicago
Toronto
location (cities)

Browsing a Data Cube



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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)

Top down or bottom up?

- Top down
  - pros: serves as systematic solution and minimizes integration problems
  - cons: expensive, long development time, lacks flexibility as a common data model for the entire organization is difficult to achieve
- Bottom up
  - pros: flexible, low cost and rapid ROI
  - cons: integration problems

Data Warehouse Design Process

- 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, e.g. individual transactions, individual daily snapshots etc.
  - Choose the dimensions that will apply to each fact table record, e.g. time, item, customer, sales etc.
  - Choose the measure that will populate each fact table record, e.g., dollars sold, units sold etc

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

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
  - 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

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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, slicing, dicing and pivoting
- Data Warehouse Architecture, Design, and Usage
  - Multi-tiered architecture
  - Business analysis design framework
  - Information processing, analytical processing, data mining, OLAM (Online Analytical Mining)

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