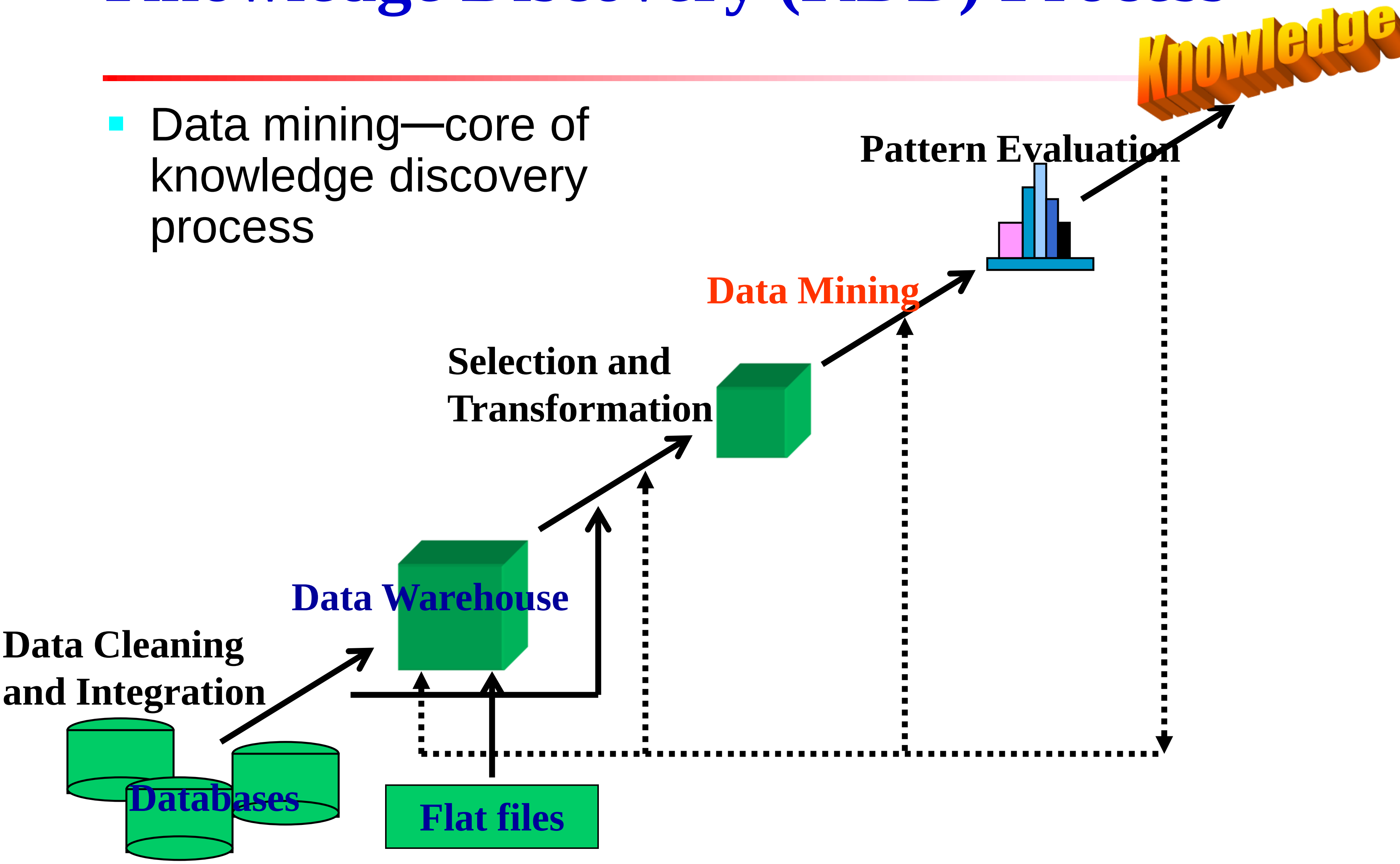
Data Mining

Ying Liu, Prof., Ph.D

School of Computer Science and Technology
University of Chinese Academy of Sciences
Data Mining and High Performance Computing Lab

Knowledge Discovery (KDD) Process

- Data mining—core of knowledge discovery process



Data Warehouse and OLAP Technology Overview

- What is a data warehouse?
- A multi-dimensional data model
- Data warehouse architecture
- Data warehouse implementation
- From data warehousing to data mining

What is Data Warehouse?

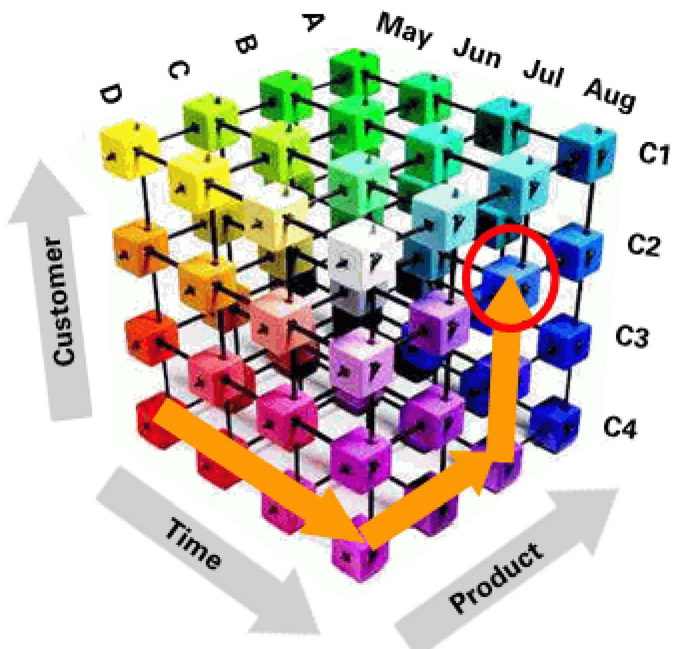
- “A data warehouse is a subject-oriented, integrated, time-variant, and nonvolatile collection of data in support of management’s decision-making process.” — W. H. Inmon
- Defined in many different ways, but not rigorously
  - A decision support database that is maintained separately from the organization’s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

Data Warehouse

- 数据仓库将分布在企业网络中不同信息岛上的业务数据集成到一起，存储在一个单一的集成关系型数据库中，利用这样的集成信息，可方便用户对信息访问，可使决策人员对一段时间内的历史数据进行分析，研究事务的发展走势—Informix 公司
- 数据仓库是一种管理技术，旨在通过通畅、合理、全面的信息管理，达到有效的决策支持—SAS软件研究所
- 数据仓库是集成信息的存储中心，这些信息可用于查询或分析—Stanford University

Example

- Customer relationship management



- Banking decision support system
- Insurance decision support system

Example

- Weather forecasting
  - Air pressure, temperature, longitude/latitude, humidity, time, etc.
  - Slice, drill down, roll up, etc.
  - Query
  - Multi-dimensional visualization

Data Warehouse—Subject-Oriented

- Organized around major subjects, such as customer, product, sales
- Focus 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
  - 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. Operational DBMS

- OLTP (on-line transaction processing)
  - Major task of traditional relational DBMS
  - Day-to-day operations: e.g. 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
  - 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

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

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, 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
- Note: There are more and more systems which perform OLAP analysis directly on relational databases

Exercise

1. For the integration of multiple heterogeneous information sources, many companies in industry prefer the *update-driven* approach (which constructs and uses data warehouses), rather than the *query-driven* approach (which applies wrappers and integrators). Please describe situations where the *query-driven* approach is preferable over the *update-driven* approach.

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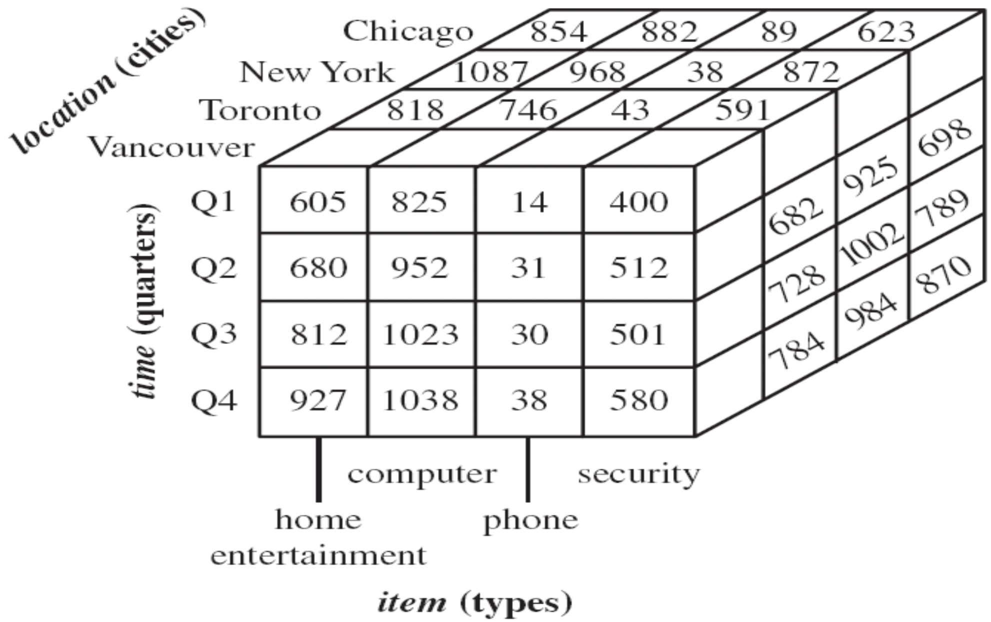
From Tables and Spreadsheets to Data Cubes

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

From Tables and Spreadsheets to Data Cubes

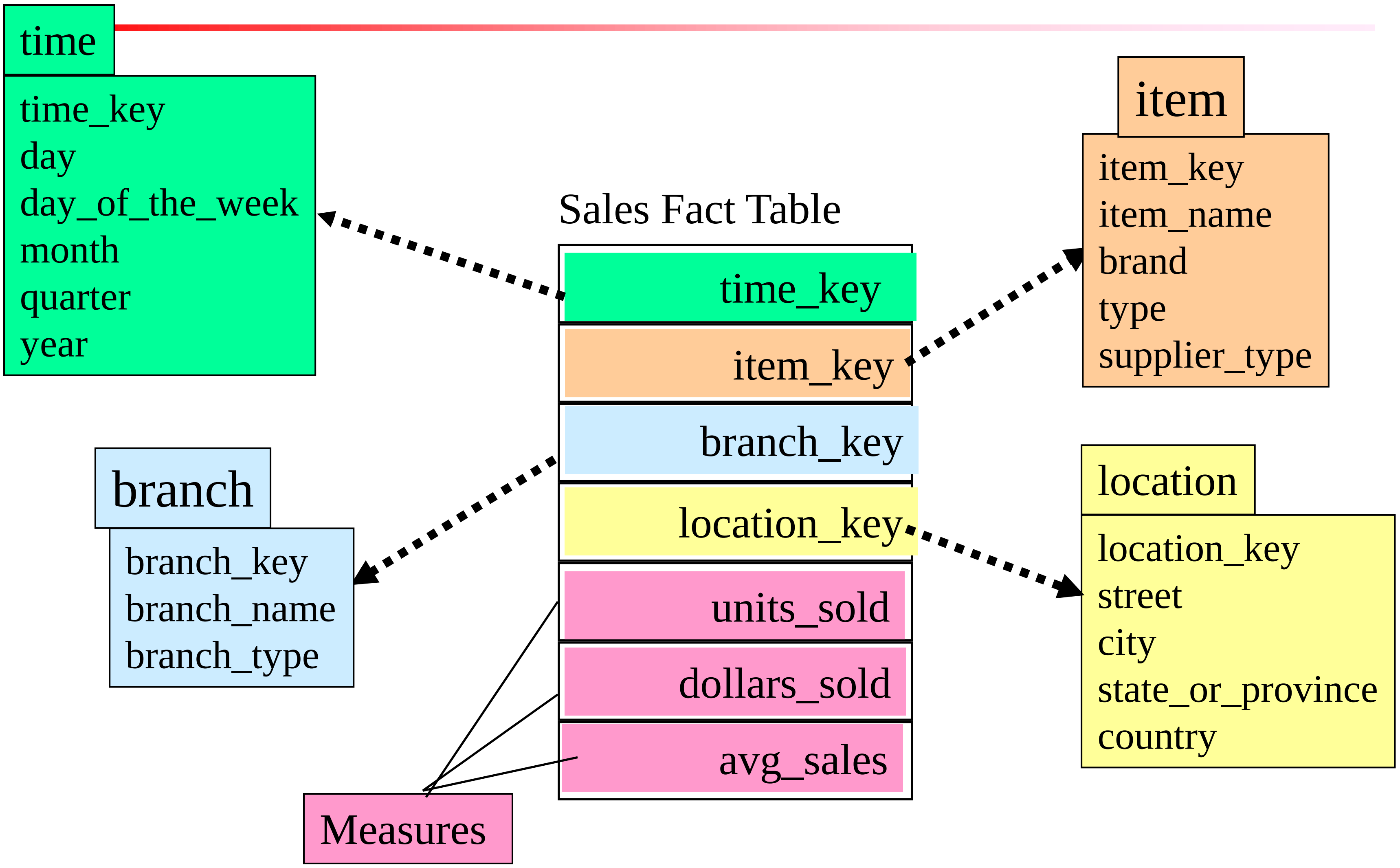
time (quarter)	*location* = "Vancouver"			
	item (type)			
	home entertainment	computer	phone	security
Q1	605	825	14	400
Q2	680	952	31	512
Q3	812	1023	30	501
Q4	927	1038	38	580



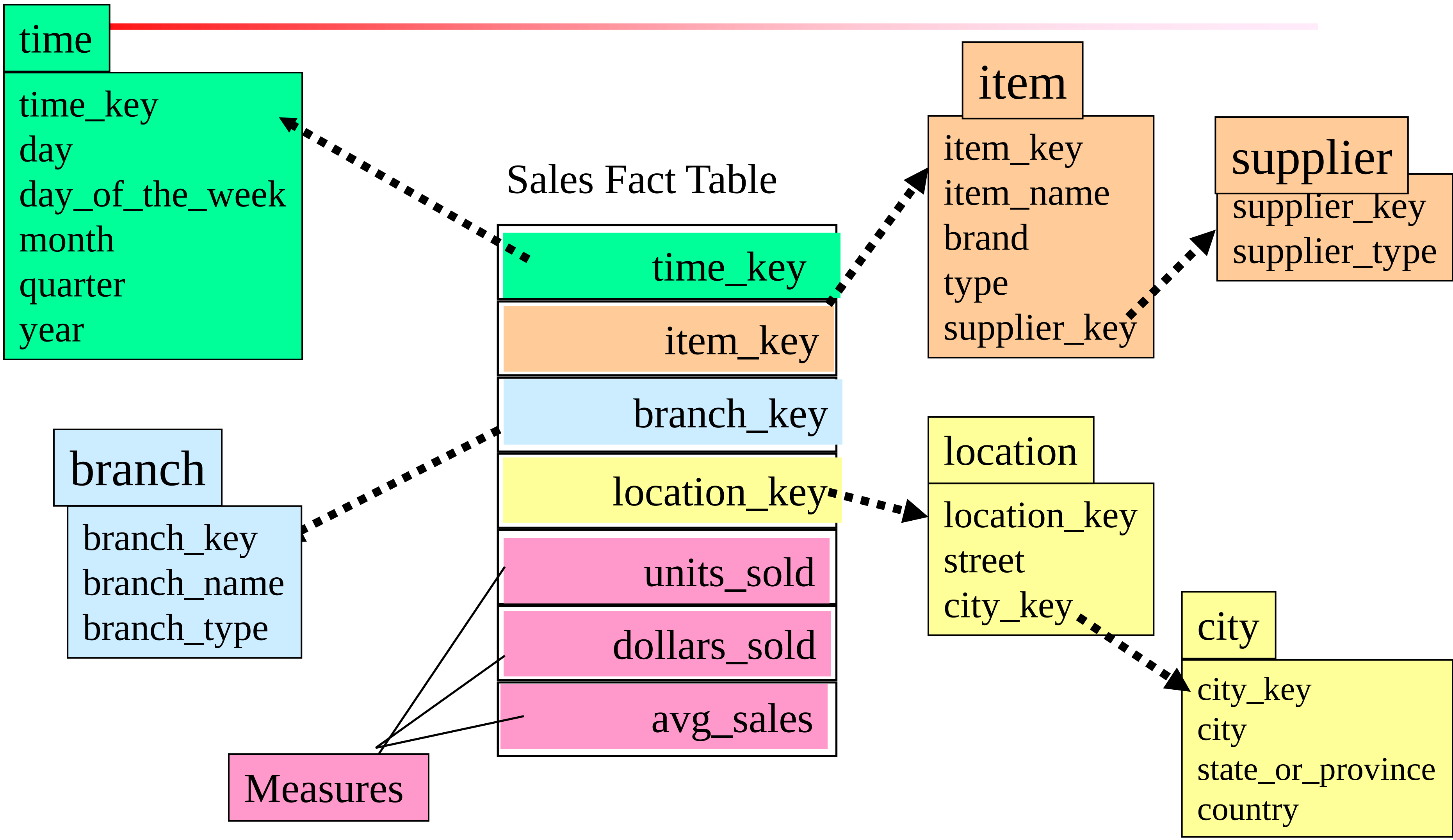
Conceptual Modeling of Data Warehouses

- 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

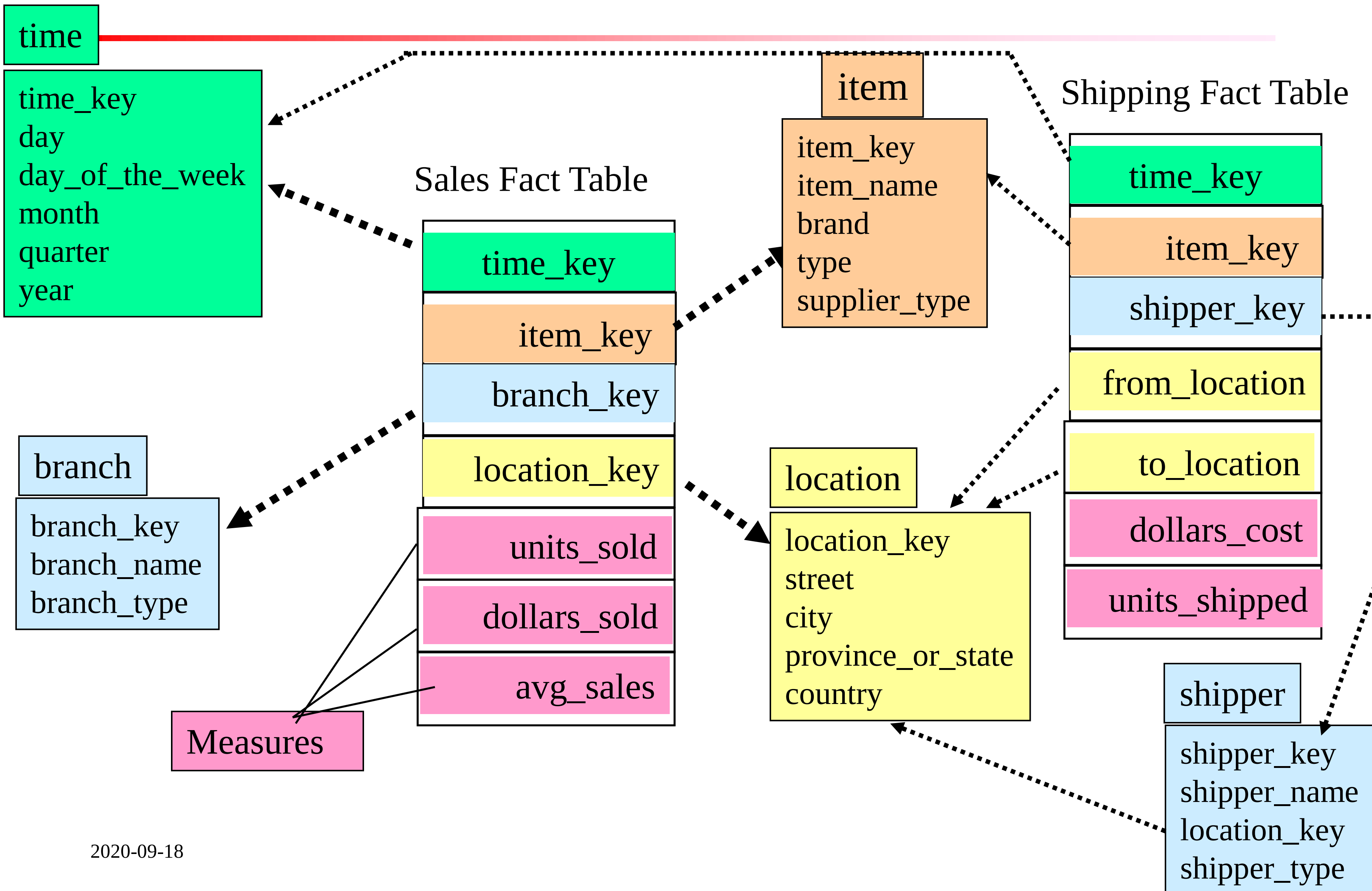
Example of Star Schema



Example of Snowflake Schema



Example of Fact Constellation



Cube Definition Syntax in DMQL

- Cube Definition (Fact Table)

  define cube <cube_name> [<dimension_list>]: <measure_list>

- Dimension Definition (Dimension Table)

  define dimension <dimension_name> as (<attribute_or_subdimension_list>)

- Special Case (Shared Dimension Tables)
  - First time as "cube definition"
  - define dimension <dimension_name> as <dimension_name_first_time> in cube <cube_name_first_time>

Defining Star Schema in DMQL

define cube sales_star [time, item, branch, location]:

dollars_sold, avg_sales, units_sold

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)

Defining Snowflake Schema in DMQL

define cube sales_snowflake [time, item, branch, location]:

dollars_sold, avg_sales, units_sold

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))

Defining Fact Constellation in DMQL

define cube sales [time, item, branch, location]:

dollars_sold, avg_sales, units_sold

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, unit_shipped

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_key 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

Exercise

1. Suppose that a data warehouse consists of three dimensions *time, doctor, and patient*, and two measures count and charge, where charge is the fee that a doctor charges a patient for a visit.

(1) Draw a schema diagram for the data warehouse.

How to Generate a Specified Data Cube?

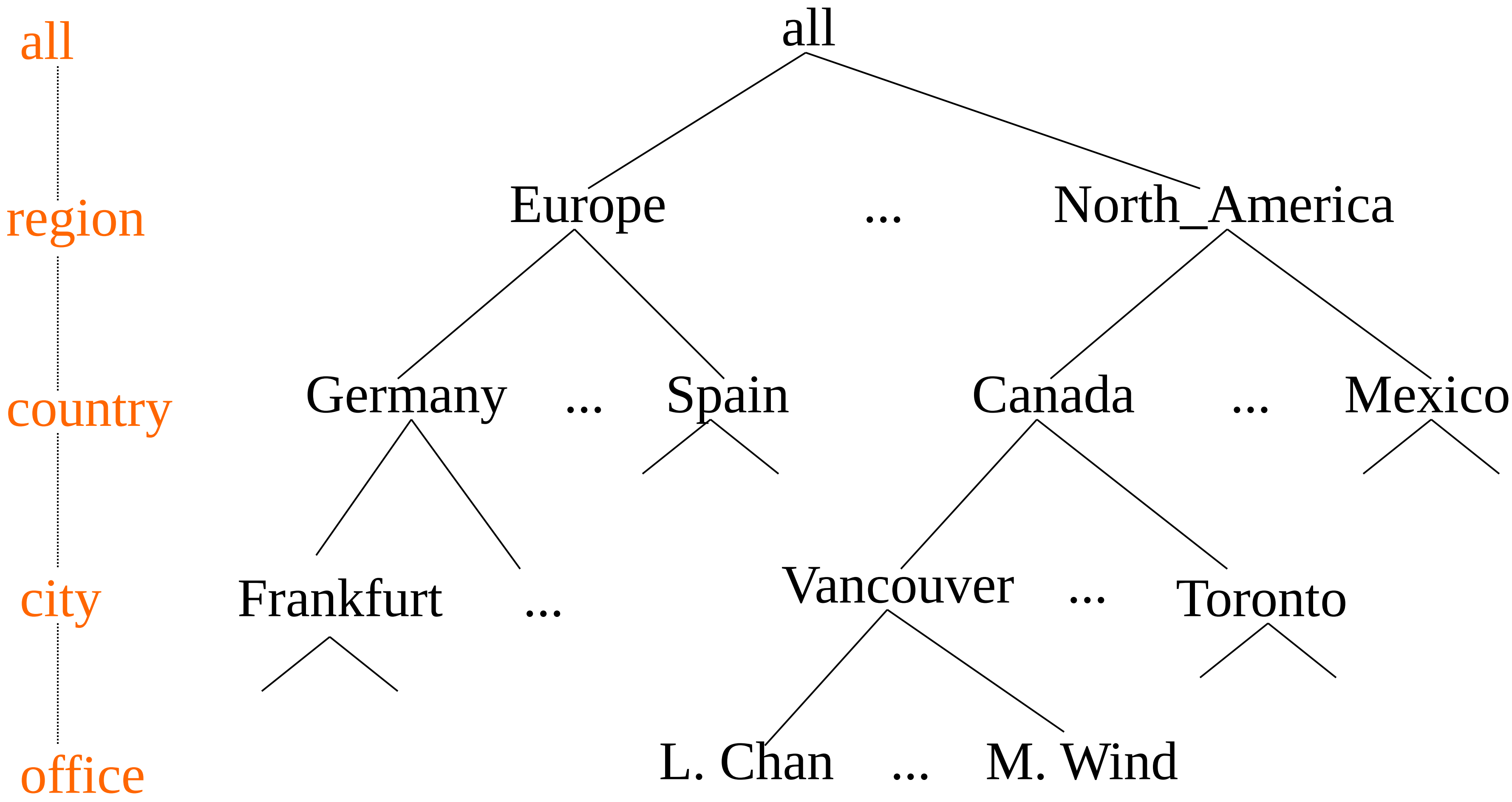
- DMQL specification is translated into SQL query

```
define cube sales_star [time, item, branch, location]:
        dollars_sold, units_sold, units_sold
```

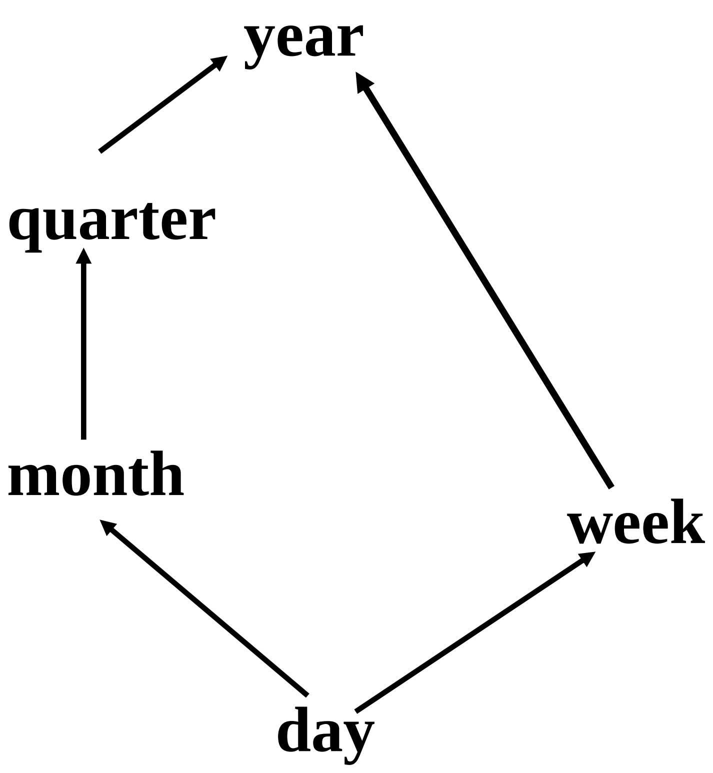
translator ⬇

```
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
```

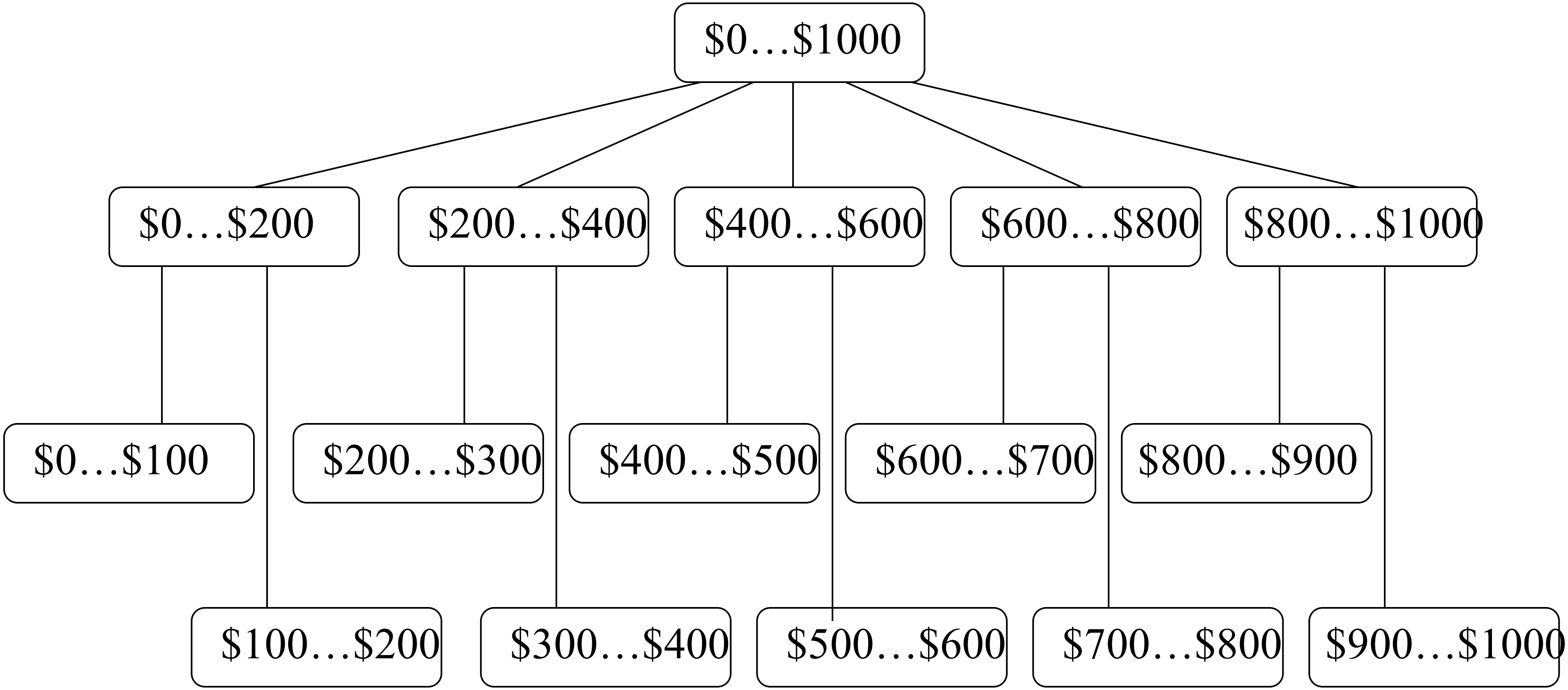
A Concept Hierarchy: Dimension (location)



A Concept Hierarchy: Dimension (time)



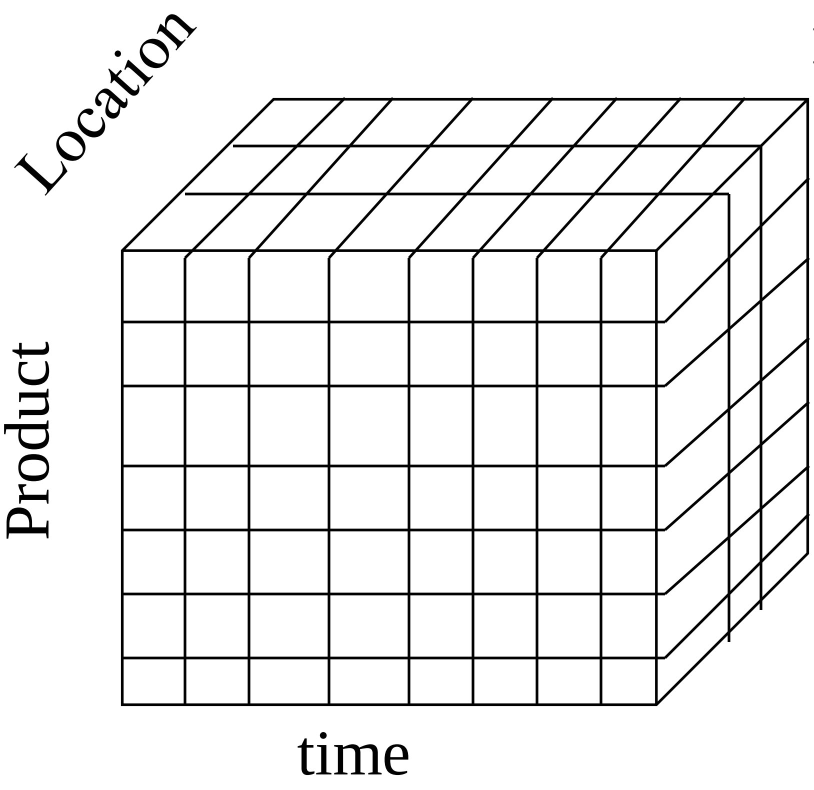
A Concept Hierarchy for Numeric Values

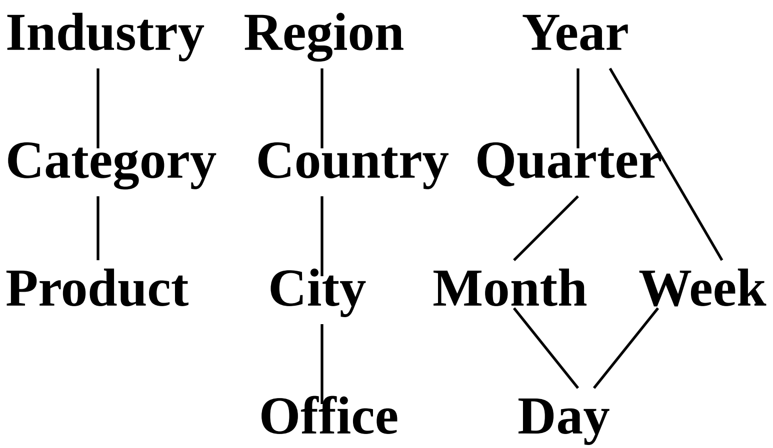


Multidimensional Data

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

Dimensions: Product, Location, Time
Hierarchical summarization paths

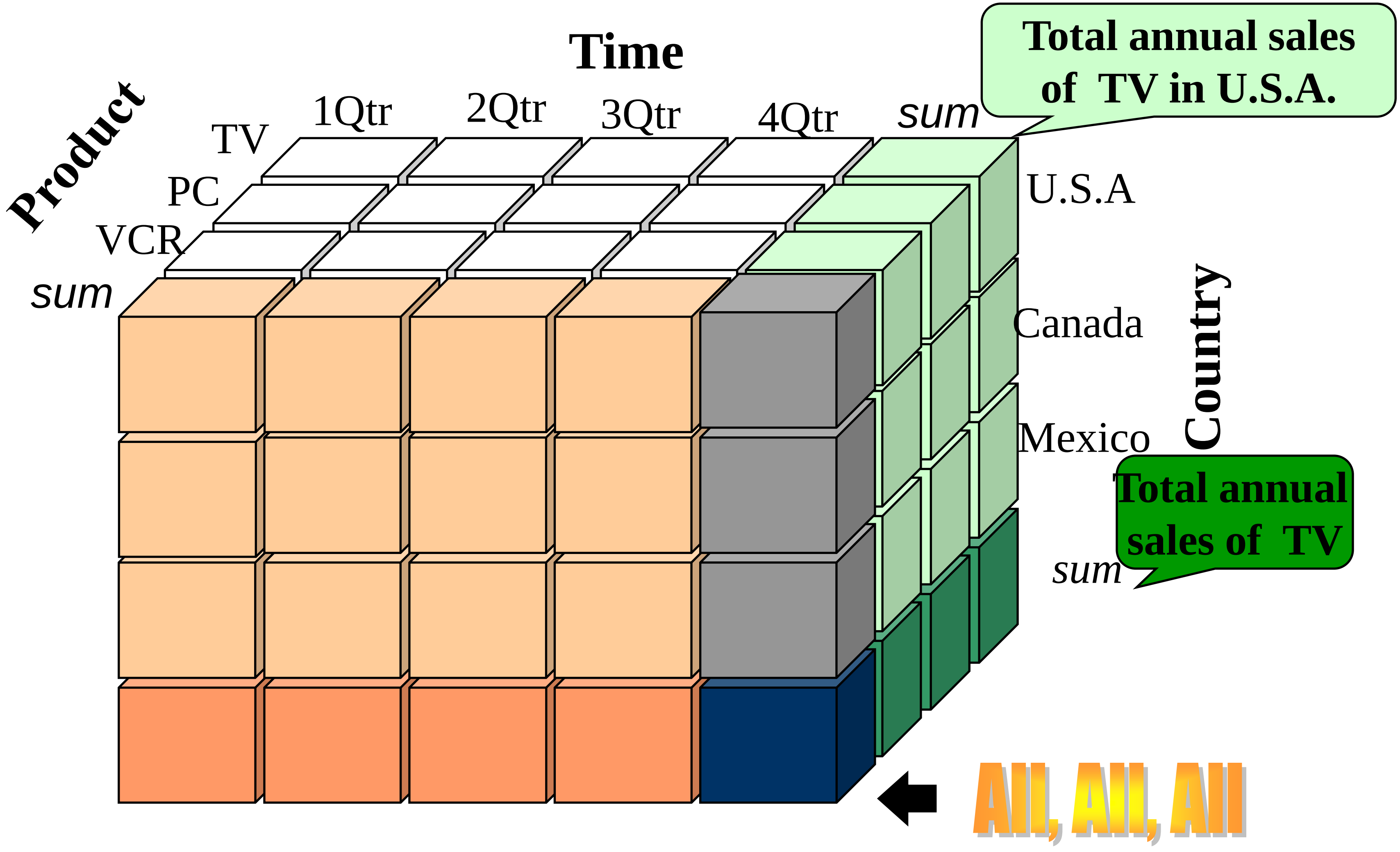


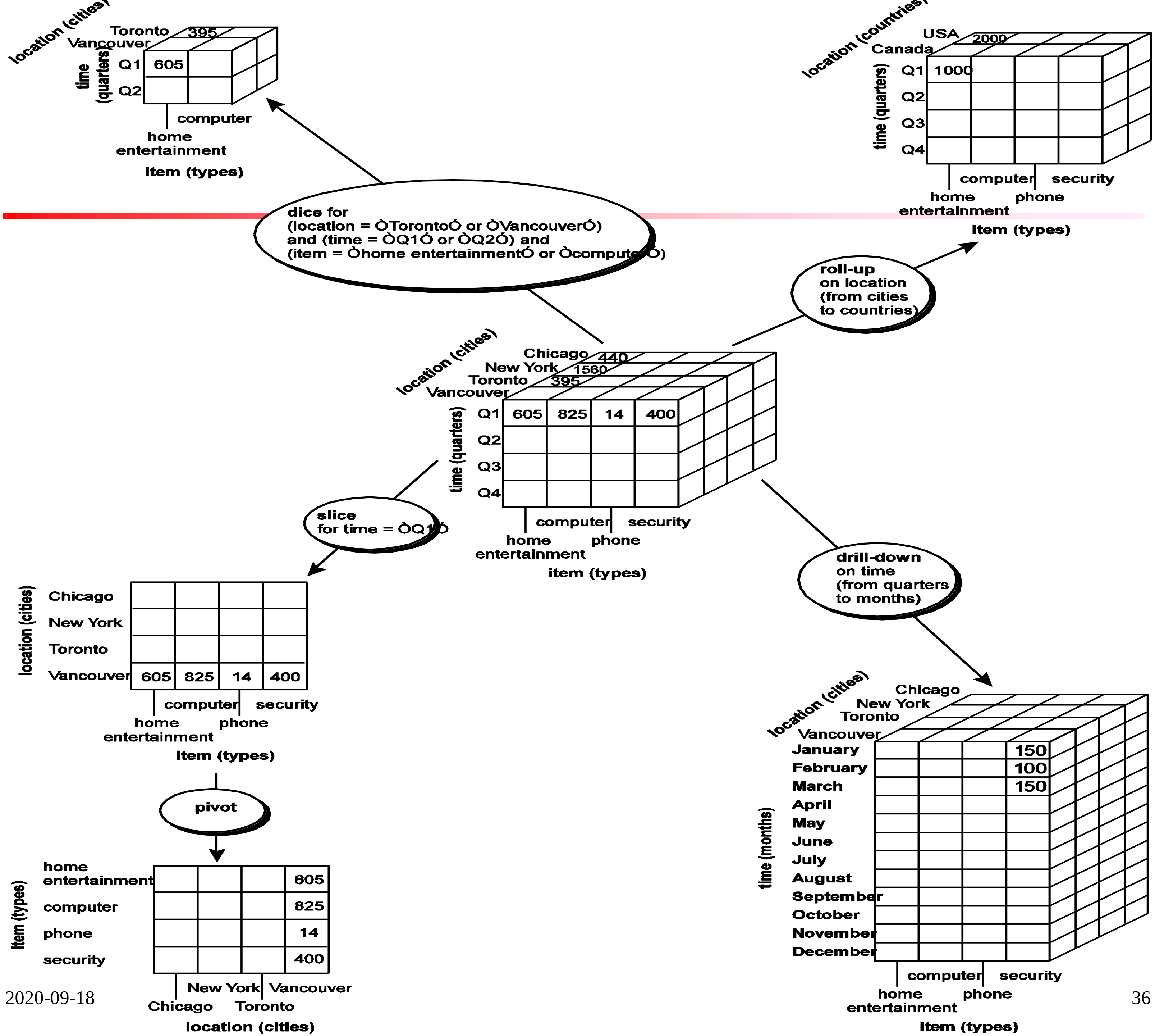


Typical OLAP Operations

- 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*

A Sample Data Cube





dice for
(location = ÒTorontoÓ or ÒVancouverÓ)
and (time = ÒQ1Ó or ÒQ2Ó) and
(item = Òhome entertainmentÓ or ÒcomputerÓ)
roll-up
on location
(from cities
to countries)
slice
for time = ÒQ1Ó
drill-down
on time
(from quarters
to months)
pivot
location (cities)
location (countries)
time (quarters)
time (months)
item (types)
Toronto
Vancouver
Chicago
New York
USA
Canada
Q1
Q2
Q3
Q4
January
February
March
April
May
June
July
August
September
October
November
December
home entertainment
computer
phone
security
395
605
2000
1000
440
1560
825
14
400
150
100

OLAP Operations

- 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)*
  - *rank top N* or *bottom N items in lists*
  - *Compute average, variance, deviation*

Exercise

1. Suppose that a data warehouse consists of three dimensions *time, doctor, and patient*, and two measures count and charge, there charge is the fee that a doctor charges a patient for a visit.

(2) Starting with the base cuboid [day, doctor, patient], what OLAP operations should be performed in order to list the total fee collected by each doctor in 1999?

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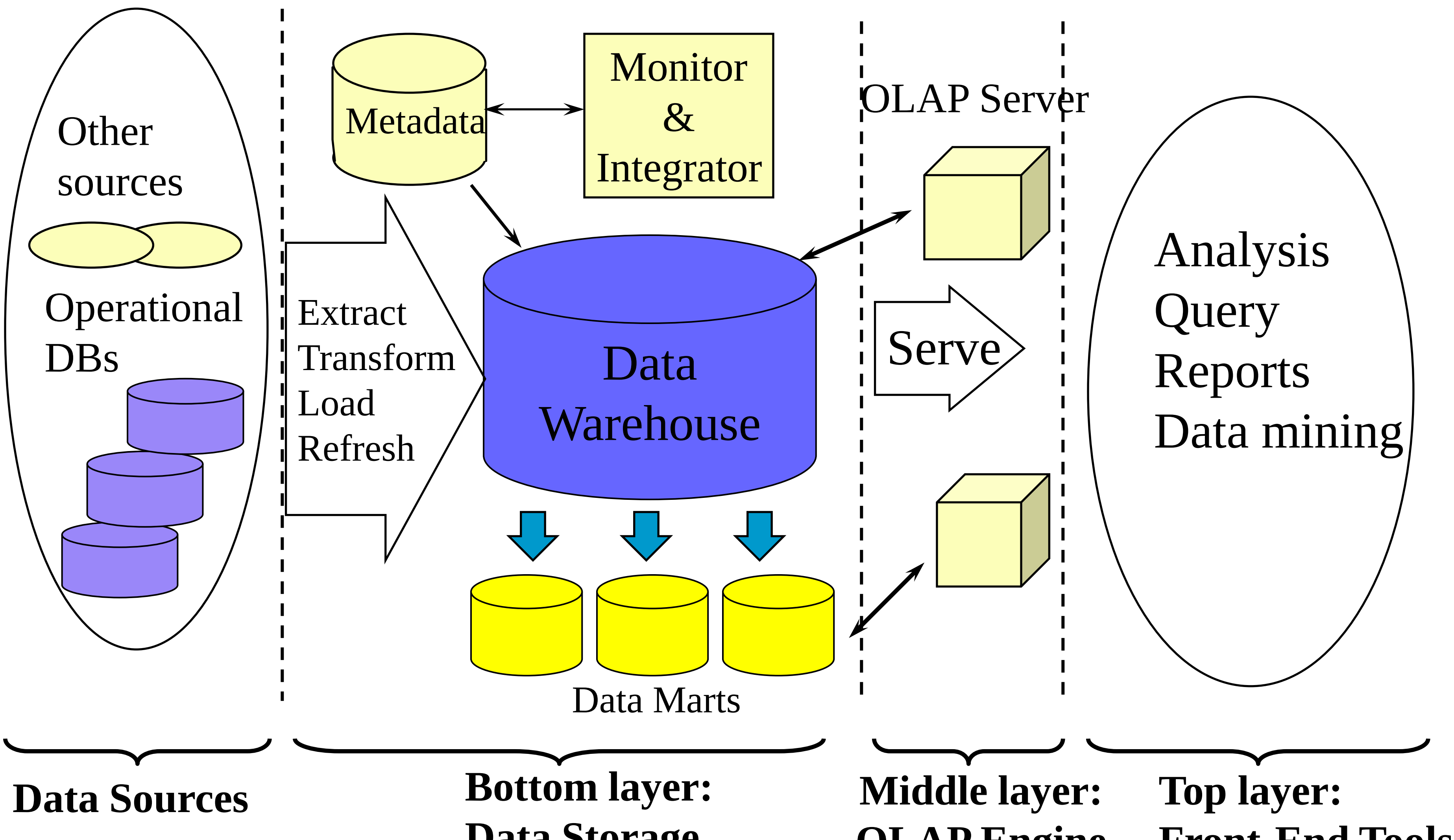
Data Warehouse: A Three-Layer Architecture



Data Warehouse Back-End Tools and Utilities

- 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
- Refresh
  - propagate the updates from the data sources to the warehouse

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 group 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

Data Mart

- Credit scoring

C_id	sex	age	income	edu	# credit cards	Payment ratio per month	# loans	Payment ratio per month	…
12	0	34	50K	BS.	1	100%	1	100%	…
14	1	29	60K	BS.	2	20%	1	50%	…
135	1	46	100K	MS.	4	100%	2	100%	…
…	…	…	…	…	…	…	…	…	…

- Utility mining

C_id	T_id	A	Profit(A)	B	Profit(B)	C	Profit(C)	D	Profit(D)	…
12	01	0	0	4	5.2	1	0.9	3	5.7	…
14	123	3	6.0	0	0	1	0.9	2	3.8	…
135	12	1	2.0	1	1.3	2	1.8	1	1.9	…
…	…	…	…	…	…	…	…	…	…	…

Metadata Repository

- Meta data is data about data. It contains:
  - Description of the structure of the data warehouse
    - schema, view, dimensions, hierarchies, derived data definition, 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)

Metadata Repository

- 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
  - Use parallel computing, bitmap indexing, etc.

OLAP Server Architectures

- Multidimensional OLAP (MOLAP)
  - Sparse array-based multidimensional storage engine
  - Fast indexing to pre-computed summarized data
  - Sparse matrix compression technique
- Hybrid OLAP (HOLAP) (e.g., Microsoft SQLServer)
  - Flexibility, e.g., low level: relational, high-level: array

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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

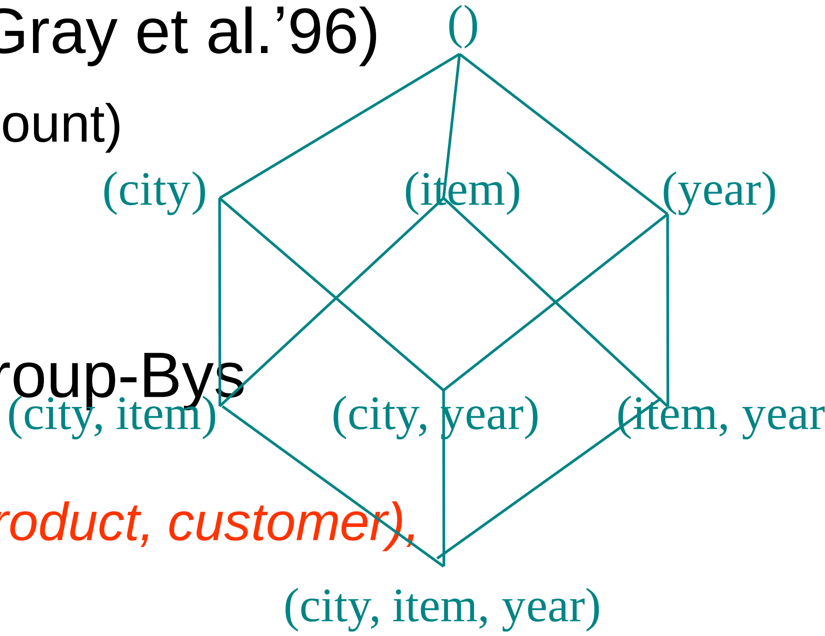
- Need to compute the following Group-Bys

    (date, product, customer),

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

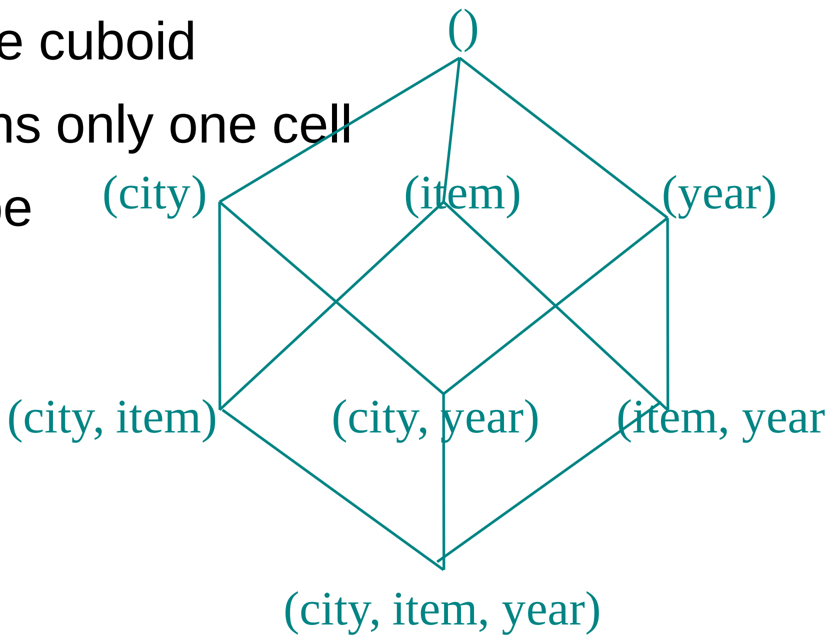
    (date), (product), (customer)

    ()



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
  - 2^n cuboids in an n-dimensional cube



- Materialization of data cube
  - 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

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

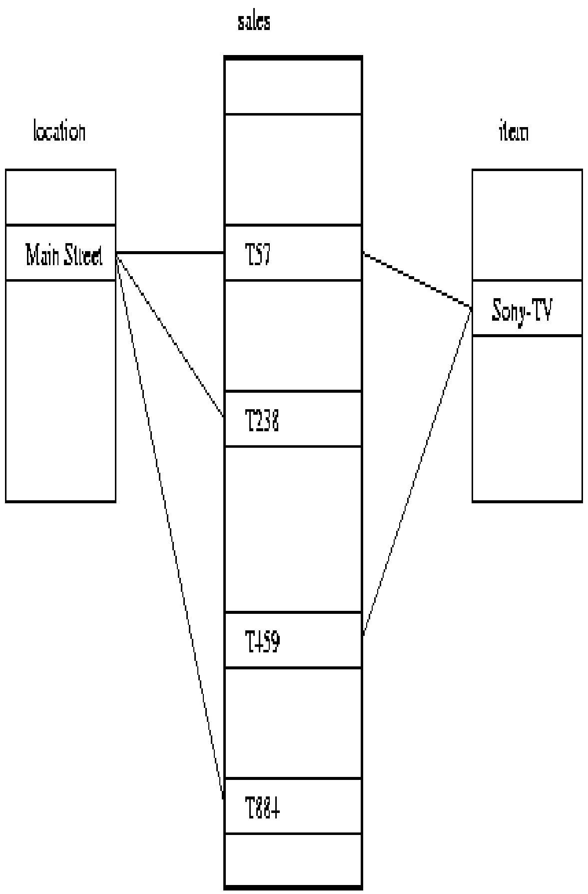
Index on Type

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

Indexing OLAP Data: Join Indices

- Join index: JI(R-id, S-id) where R (R-id, …) $\triangleright\triangleleft$ S (S-id, …)
- Traditional indices map the values to a list of record ids
  - It materializes relational join in Join Index 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

Indexing OLAP Data: Join Indices



Join index table for
location/sales

location	*sales_key*
. . .	. . .
Main Street	T57
Main Street	T238
Main Street	T884
. . .	. . .

Join index table for
item/sales

item	*sales_key*
. . .	. . .
Sony-TV	T57
Sony-TV	T459
. . .	. . .

Join index table linking two dimensions
location/item/sales

location	*item*	*sales_key*
. . .	. . .	. . .
Main Street	Sony-TV	T57
. . .	. . .	. . .

Exercise

1. Suppose a data warehouse for *Big_University* consists of four dimensions *student, course, semester, and instructor*, and two measures *count* and *score*.

(a) Draw a snowflake schema diagram for this data warehouse.

(b) Starting with the base cuboid [*student, course, semester, instructor*], what specific OLAP operations should you perform to list the number of CS courses for each *Big_University* student?

(c) If each dimension has five concept levels (including *all*), such as "*student* < *major* < *status* < *university* < *all*", how many cuboids will this cube contain?

(d) Taking this cube as an example, discuss advantages and problems of using a bitmap index structure.

Exercise

2. Suppose a data warehouse has 20 dimensions, each with five concept levels.

(a) Users are mainly interested in four particular dimensions, each having three frequently accessed levels for rolling up and drilling down. How would you design a data cube to efficiently support this preference?

(b) Occasionally, a user may want to drill through the cube down to its raw relational database for one or two particular dimensions. How would you support this feature?

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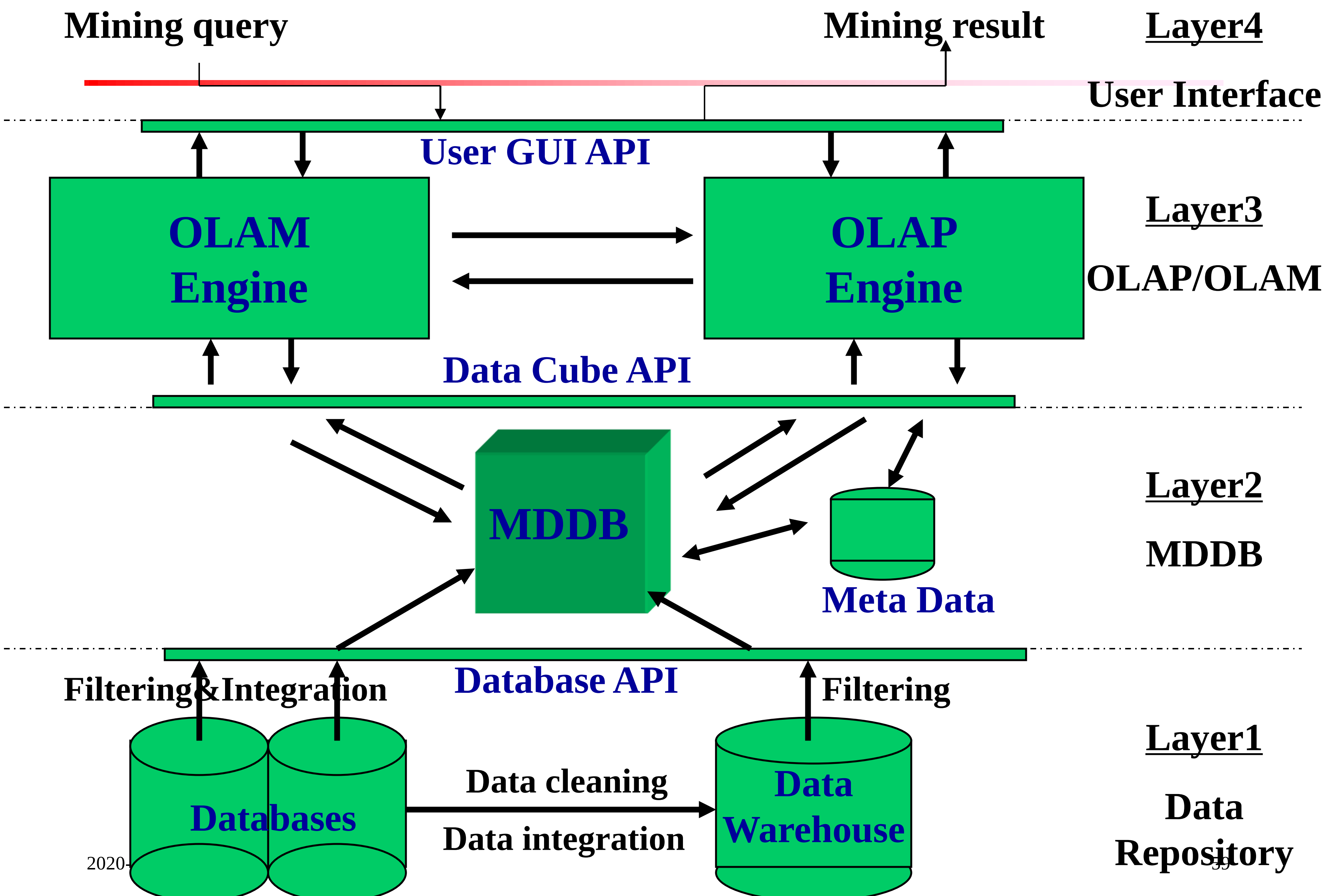
Data Warehouse Usage

- Three kinds of data warehouse applications
  - Information processing
    - supports querying, basic statistical analysis, and reporting using crosstabs, tables, charts and graphs
  - Analytical processing
    - 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
  - 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

An OLAM System Architecture



Summary

- Why data warehousing?
- A multi-dimensional model of a data warehouse
  - Star schema, snowflake schema, fact constellations
  - A data cube consists of dimensions & measures
- OLAP operations: drilling, rolling, slicing, dicing and pivoting
- Data warehouse architecture
- OLAP servers: ROLAP, MOLAP, HOLAP
- Efficient computation of data cubes
  - Partial vs. full vs. no materialization
  - Indexing OALP data: Bitmap index and join index
- From OLAP to OLAM (on-line analytical mining)