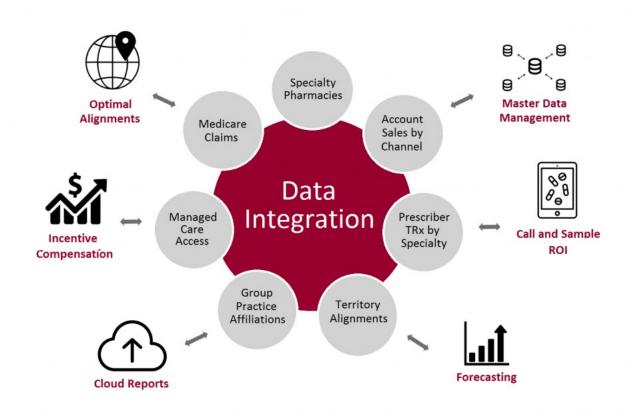
Chapter 3 Data modelling and databases OLTP & OLAP

Outline

- Overview
- OLTP vs OLAP
- Data warehouse modeling
- Data warehouse design



Heterogeneous data sources





Why data integration

- To facilitate information access and reuse through a single information access point
- Data from different complementing information systems is to be combined to gain a more comprehensive basis to satisfy the need
 - Improve decision making
 - Improve customer experience
 - Increase competitiveness, Streamline operations
 - Increase productivity
 - Predict the future



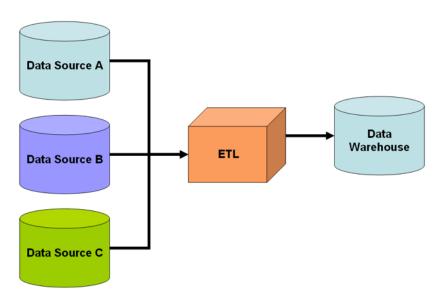
Data integration challenges

- Physical systems
 - Various hardwares, standards
 - Distributed deployment
 - Various data format
- Logical structures
 - Different data models
 - Different data schemas
- Business organization
 - Data security and privacy
 - Business rules and requirements
 - Different administrative zones in the business organization



Data Warehouse

- A single, complete and consistent store of data obtained from a variety of different sources made available to end users in a what they can understand and use in a business context. [Barry Devlin]
- A data warehouse is a copy of transaction data specifically structured for query and analysis [Ralph Kimball]
- Data from several operational sources (OLTP) are extracted, transformed, and loaded (ETL) into a data warehouse



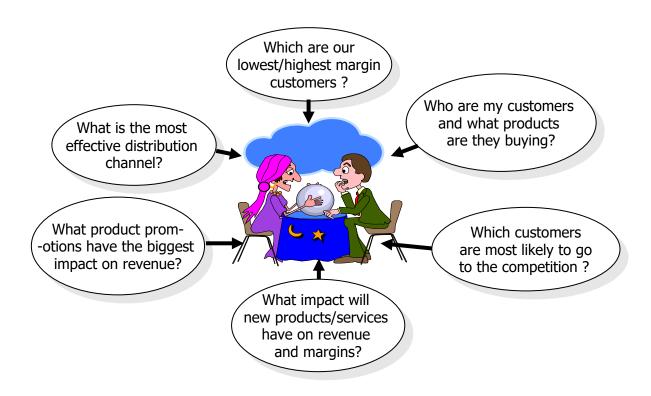


Data Warehouse usage

- 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



Data Warehouse usage



Advantages

- High query performance
 - But not necessary most current information
- Does not interfere with local processing at sources
 - Complex queries at warehouse
 - OLTP at information sources



Characteristics of Data warehouse

- Subject-Oriented
- Integrated
- Time-variant
- Non-volatile



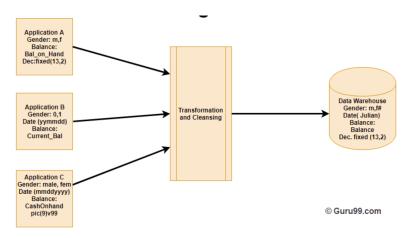
Subject-Oriented

- Offer information regarding a theme instead of companies' ongoing operations
 - Subjects can be sales, marketing, distributions, etc.
 - A data warehouse never focuses on the ongoing operations
- Emphasis on modeling and analysis of data for decision making
 - Provide a simple and concise view around the specific subject by excluding data which not helpful



Integrated

- Constructed by integrating multiple, heterogeneous data sources
 - Data needs to be stored in the Datawarehouse in a common and universally acceptable manner
 - This integration helps in effective analysis of data
- 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.





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 is loaded daily, hourly, or on some other periodic basis, and does not change within that period



Time Data
01/97 Data for January
02/97 Data for February
03/97 Data for March

03/97 Data for March

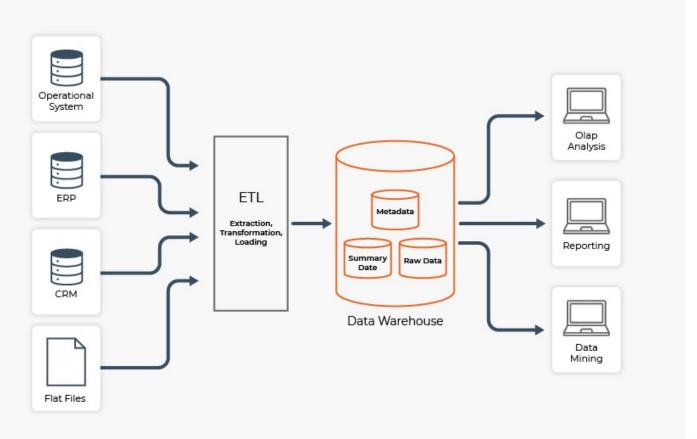
Non-volatile

- Historical data in a data warehouse should never be altered
 - Helps to analyze historical data and understand what & when happened
- Data is read-only
 - Does not require transaction process, recovery and concurrency control mechanisms
 - Delete, update, and insert are omitted
- Only two types of data operations
 - Data loading
 - Data access (reading)



Data Warehousing

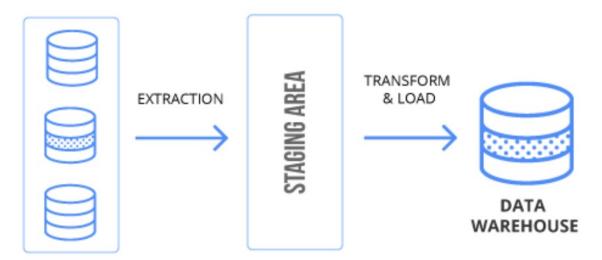
 A process for assembling and managing data from various sources for the purpose of answering business questions





ETL

- Extract
 - Get the data from source system as efficiently as possible
- Transform
 - Perform calculations on data
- Load
 - Load the data in the target storage





Staging area

- An intermediate storage area used for data processing during the extract, transform and load (ETL) process
- Mainly required for timing reasons (optional)
 - If it is not feasible to extract all the data from all Operational databases at exactly the same time
- Objectives
 - Consolidation: as a large "bucket" in which data from multiple source systems can be temporarily placed for further processing
 - Alignment: standardization of reference data, validation of relationships between records and data elements from different sources
 - Minimizing contention: efficient data transfer from sources
 - Independent scheduling
 - Change detection
 - Cleansing data



Why is ETL (System) Important?

- Adds value to data
 - Removes mistakes and corrects data
 - Documented measures of confidence in data
 - Captures the flow of transactional data
 - Adjusts data from multiple sources to be used together (conforming)
 - Structures data to be usable by BI tools
 - Enables subsequent business / analytical data procesing



Metadata Repository

- Metadata 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



OLTP vs OLAP



OLTP (Online Transaction processing)

- OLTP is characterized by a large number of short online transactions (INSERT, UPDATE, DELETE).
- The main emphasis for OLTP systems is put on very fast query processing, maintaining data integrity in multi-access environments and an effectiveness measured by number of transactions per second.
- In OLTP database there is detailed and current data, and schema used to store transactional databases is the entity model (usually 3NF).



OLAP (Online analytical processing)

- Is characterized by relatively low volume of transactions.
- Queries are often very complex and involve aggregations.
- For OLAP systems a response time is an effectiveness measure.
- OLAP applications are widely used by Data Mining techniques.
- In OLAP database there is aggregated, historical data, stored in multi-dimensional schemas (usually star schema).



OLTP vs OLAP

- targets one specific process
- Many short transactions (queries + updates)
- Examples
 - Update account balance
 - Enroll in course
 - Add book to shopping cart
- Queries touch a small amounts of data (one record or a few records)
- Updates are frequent
- Concurrency is biggest performance concern

- integrates data from different processes
- often makes use of historical data
- Long transactions, complex, ad hoc queries
- Examples
 - Report total sales for each department in each month
 - Identify top selling books
- Queries touch large amounts of data
- Updates are infrequent
- Individual queries can require lots of resources



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	



OLAP & OLTP: Different performance requirements

- Transaction processing (OLTP)
 - Fast response time important
 - Data must be up-to-date, consistent at all times
- Data analysis (OLAP)
 - Queries can consume lots of resources
 - Operating on static "snapshot" of data
- OLAP queries would degrade operational DB
 - Analysis query asks for sum of all sales
 - Acquires lock on sales table
 - New sales transaction is blocked



OLAP & OLTP: Different data modeling requirements

OLTP

- Normalized schema for consistency
- Complex data models, many tables
- Limited number of standardized queries and updates

OLAP

- Simplicity of data model is important
- De-normalized schemas are common
 - Fewer joins -> improved query performance
 - Fewer tables -> schema is easier to understand



Data Warehouse Modeling

Data Cube and OLAP models and operations



Multi-dimensional data model

- A data warehouse is based on a multidimensional data model, which views data in the form of a data cube.
 - optimized for very quick data analysis
- A data cube allows data to be modeled and viewed in multiple dimensions.
 - Fact tables contain measures of interest (such as dollars) sold) and keys to each of the related dimension tables.
 - Dimension tables provide the context of the measures such as item (item name, brand), product, location or time(day, week, month, quarter, year).



Multi-dimensional data representation

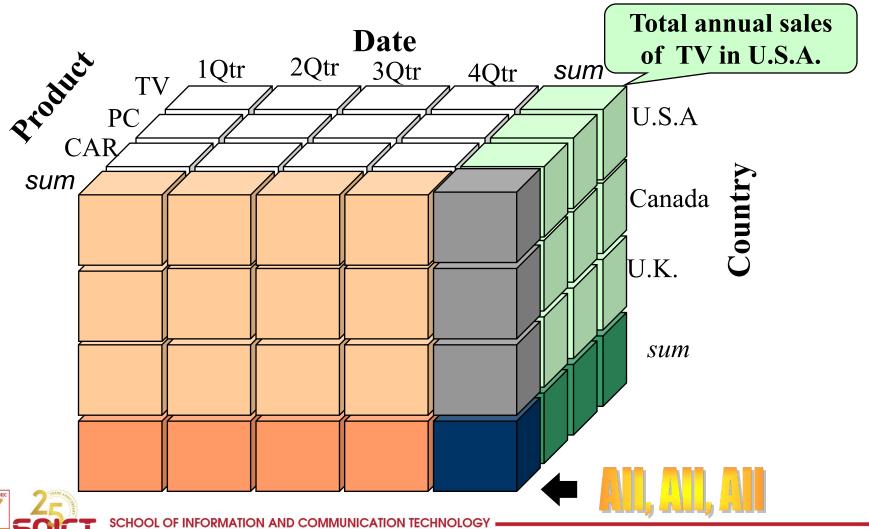
Relational table only represents multi-dimensional data in two dimensions

ID	Product	Country	Date	Sales
1	TV	US	1Qtr	100
2	PC	Canada	4Qtr	500
3	CAR	US	2Qtr	30
4	PC	UK	3Qtr	200
5	CAR	UK	1Qtr	20
6	CAR	UK	2Qtr	15
7	TV	Canada	4Qtr	80

- Cube represents data as cells in an array
 - Each side of cube is a dimension



From Tables to Data Cubes

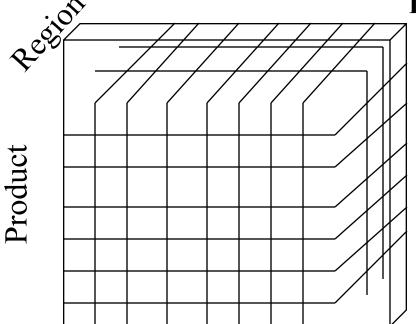


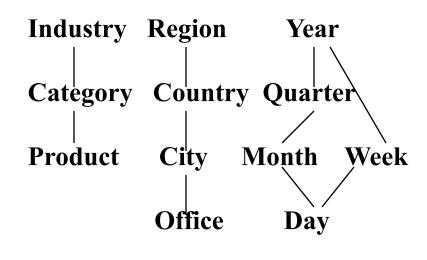
Multidimensional Data

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

• For each dimension, the set of values can be organized in a hierarchy Dimensions: *Product, Location, Time*

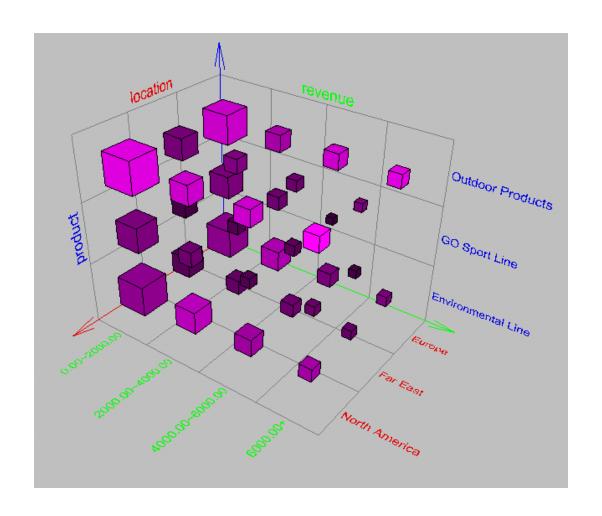
Hierarchical summarization paths





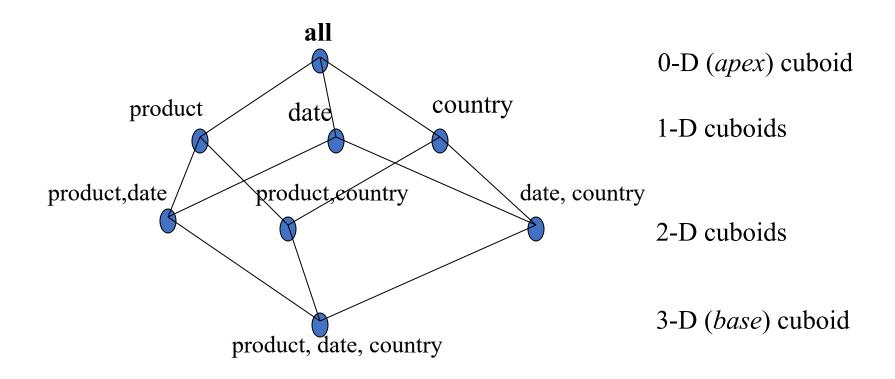


Browsing a Data Cube



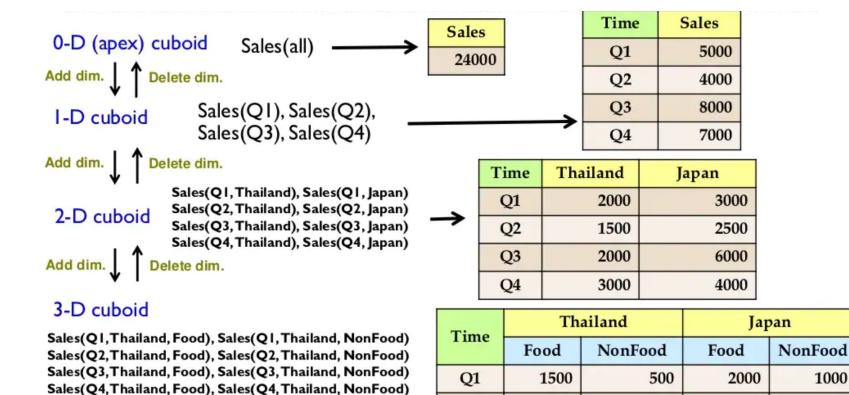


Cube: A Lattice of Cuboids





An example of cuboids



Q2

Q3

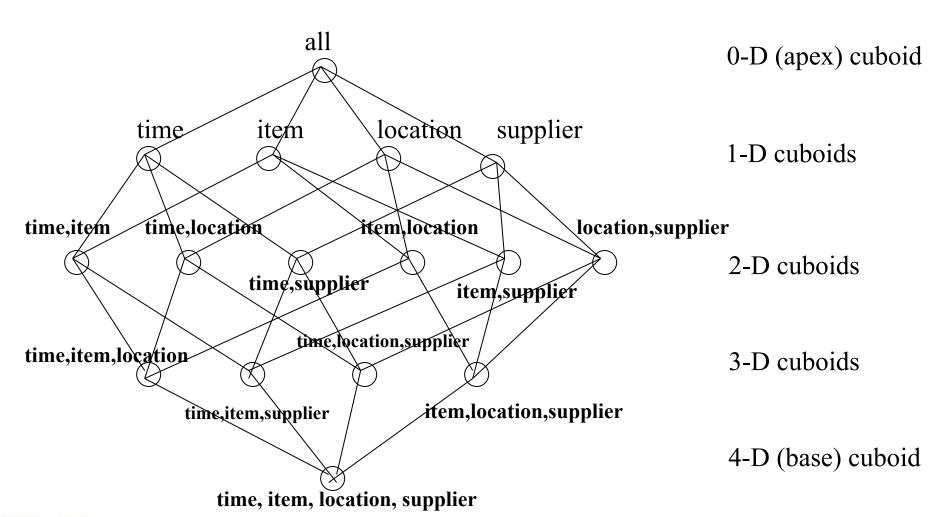


Sales(QI, Japan, Food), Sales(QI, Japan, NonFood)

Sales(Q2, Japan, Food), Sales(Q2, Japan, NonFood)

Sales(Q3, Japan, Food), Sales(Q3, Japan, NonFood) Sales(Q4, Japan, Food), Sales(Q4, Japan, NonFood)

Cube: A Lattice of Cuboids



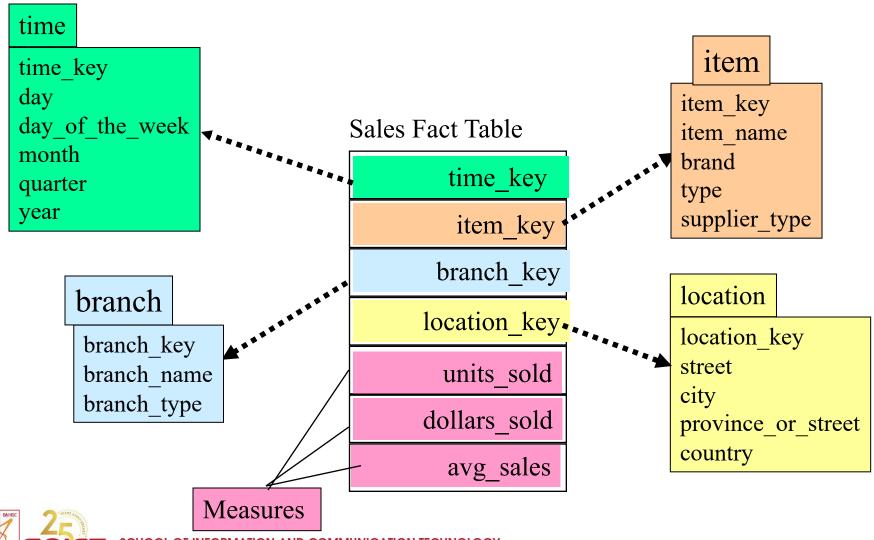


Data Warehouse Schemas (Conceptual)

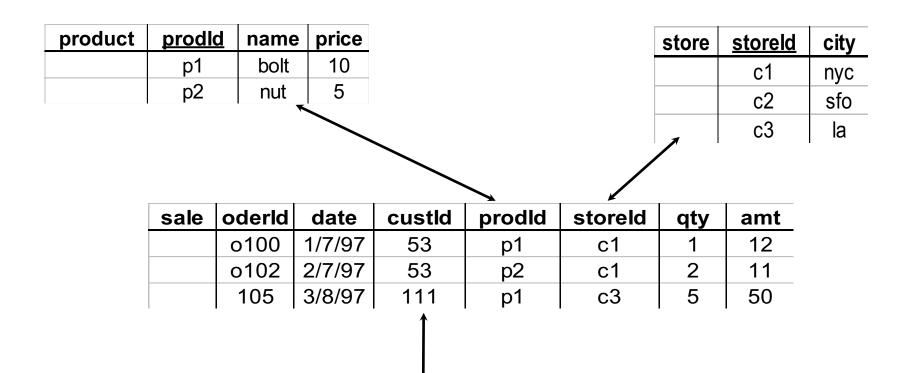
- Star Schema
 - A fact table in the middle connected to a set of dimension. tables
- Snowflake Schema
 - A refinement of star schema where some dimensional hierarchy is normalized into a set of smaller dimension tables, forming a shape similar to snowflake
- Fact Constellations
 - Multiple fact tables sharing dimension tables, viewed as a collection of stars, therefore called galaxy schema or fact constellation



The Star Schema



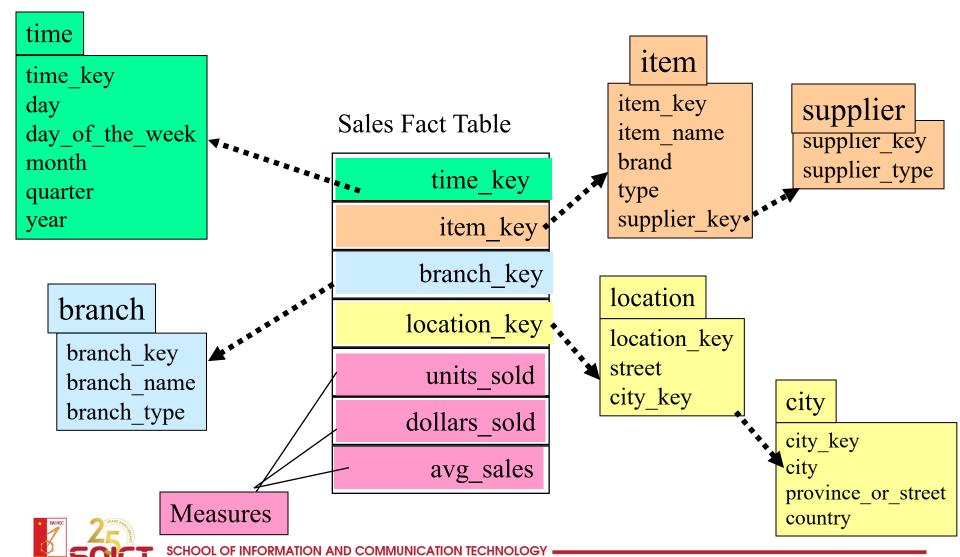
The Star Schema: An Example



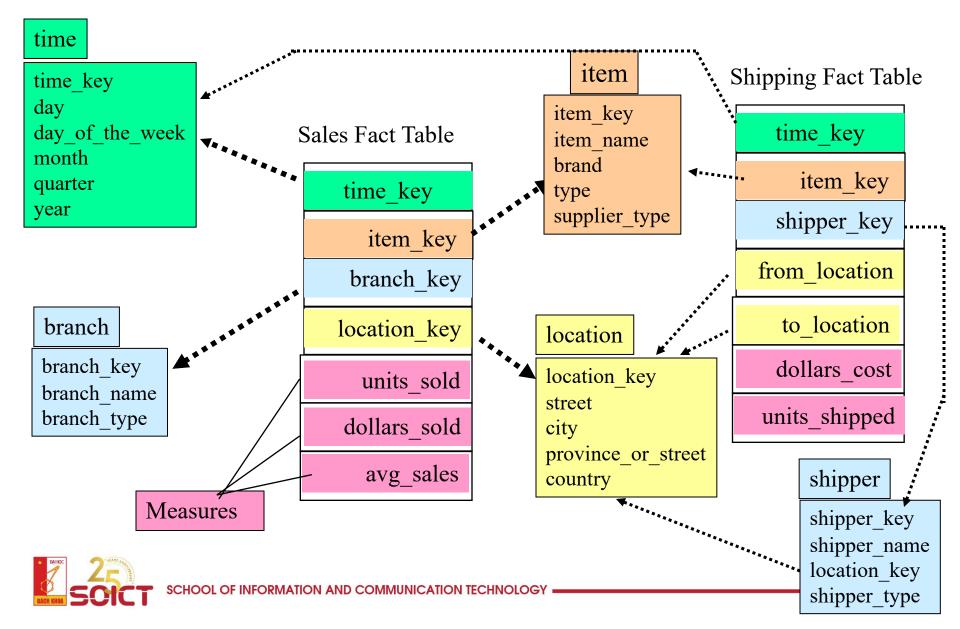
customer	<u>custld</u> name		address	city	
	53	joe	10 main	sfo	
	81	fred	12 main	sfo	
	111	sally	80 willow	la	



The Snowflake Schema



The Fact Constellation Schema



Concept Hierarchy

 Define a sequence of mappings from a set of very sepecific, low-level concepts to more general, higherlevel concepts

 E.g. concept of Location Location all North_America Europe region Canada Germany ... Spain country Vançouver... Frankfurt ... **Toronto** Chan ... M. Wind office

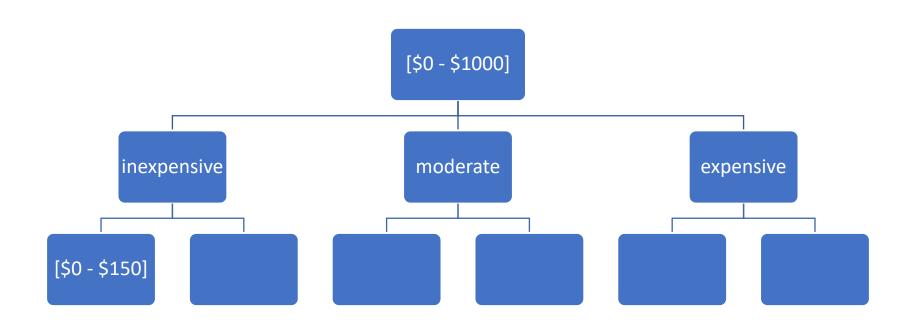


Concept Hierarchy

- Concept hierarchies are useful to perform OLAP
 - Data are organized in multiple dimensions where each dimension contains multiple levels of abstraction defined by concept hierarchies
 - It give flexibility to summarize data on various levels of granularity
 - And OLAP operations enable materialization of such views



Set-Grouping Hierarchy



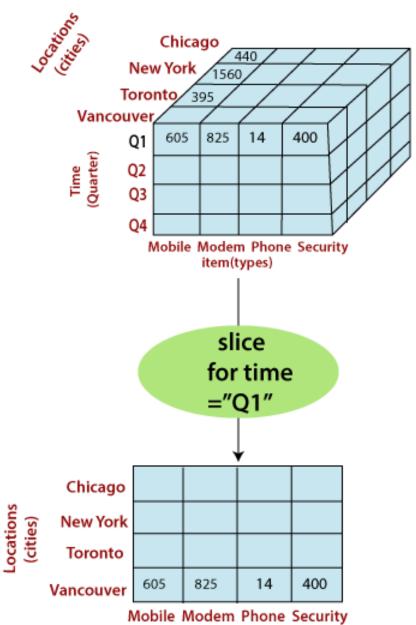


Typical OLAP Operations

- 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

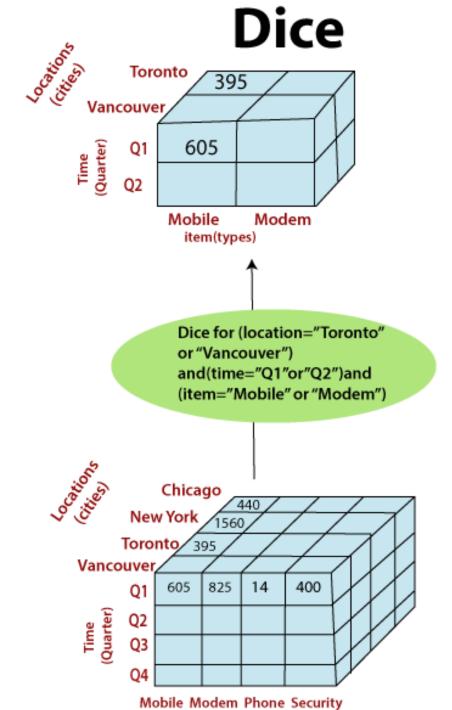


Slice





item(types)





Roll-Up & Drill-Down

Higher Level of Aggregation

Roll Up

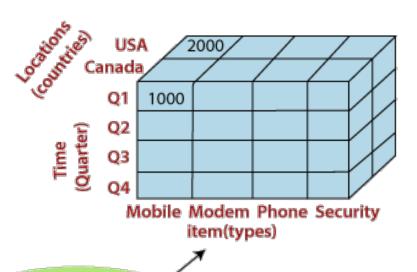
- Sales Channel
- Region
- Country
- State
- Location Address
- Sales Representative

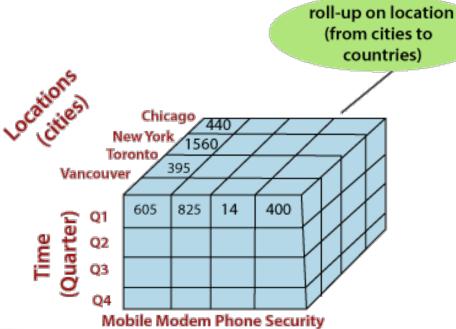
Drill-Down

Low-level Details



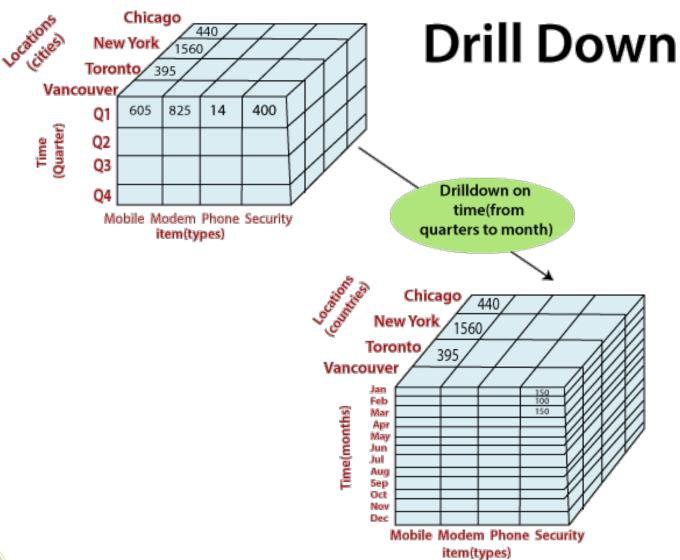
Roll UP





item(types)

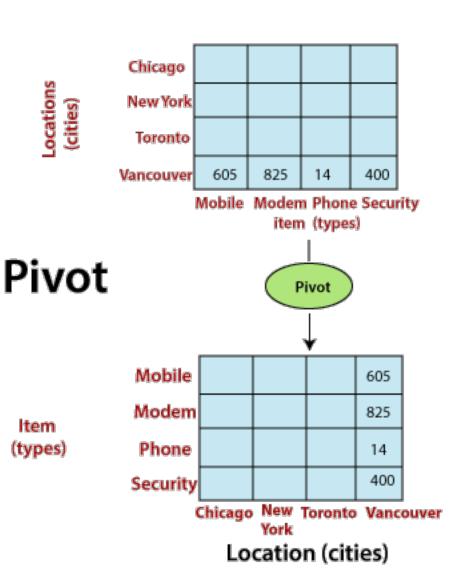






Pivot (1)

- Pivot is also called a rotation.
- Pivot rotates the data axes in view to provide an alternative presentation of the data.
- It may contain swapping the rows and columns or moving one of the row-dimensions into the column dimensions.



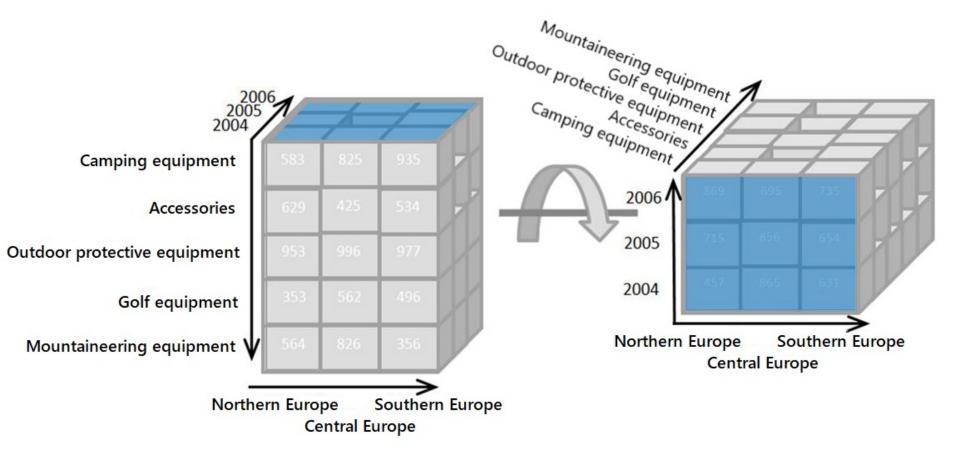


ocations

Item

(types)

Pivot (2)

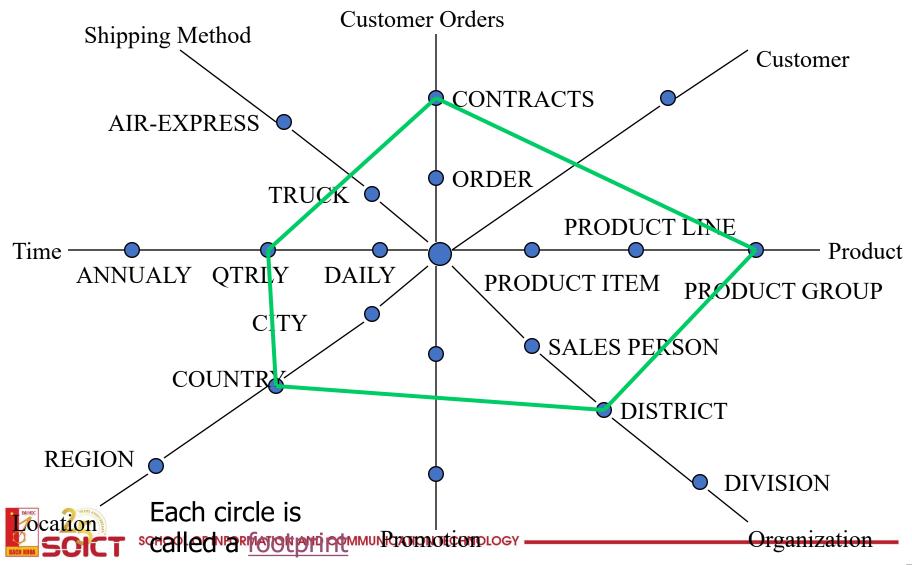




Pivot (3)

ORDERID	PRODUC	VARIANT	QUANTITY	PRODUC	Blue	Red	White
1	Helmets	Blue	10	Helmets	Σ	Σ	Σ
2	Helmets	White	5	Caps	Σ	Σ	Σ
3	Helmets	Red	20	Chapeau	Σ	Σ	Σ
4	Caps	Red	15				
5	Chapeau	White	10				
6	Chapeau	Red	30				
7	Helmets	White	5				
8	Caps	Red	5				
		$\overline{}$					

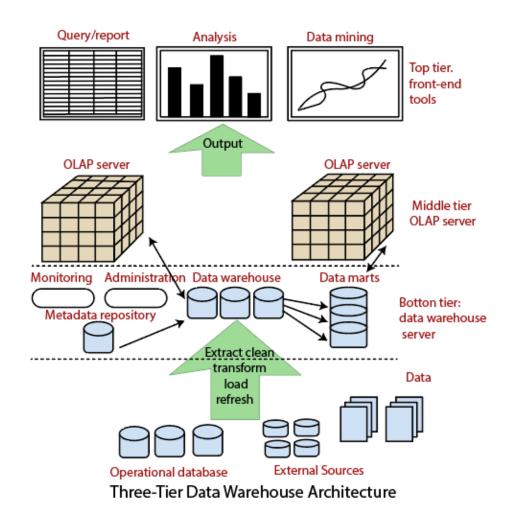
A Star-Net Query Model



Data Warehouse Design



3-tier data warehouse architecture



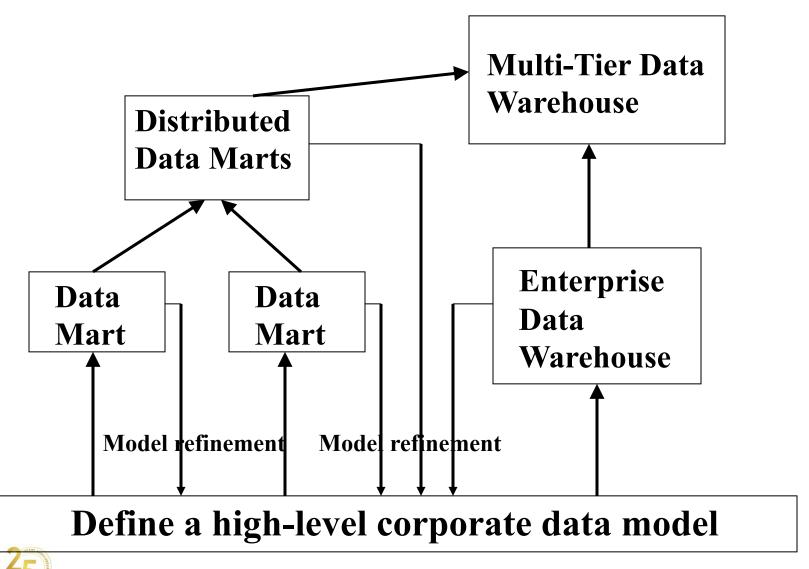


Enterprise warehouse & data marts

- Enterprise warehouse
 - collects all of the information about subjects spanning the entire organization
- Data mart
 - Holds data only for a specific department or line of business, such as sales, finance, or human resources.
 - A data warehouse can feed data to a data mart
 - A data mart can feed a data warehouse.



A Recommended Approach



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
- Implementation: Efficient computation of data cubes
 - Partial vs. full vs. no materialization
 - Indexing OALP data: Bitmap index and join index
 - OLAP query processing
 - OLAP servers: ROLAP, MOLAP, HOLAP



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