ISIT312 Big Data Management

Data Warehouse Concepts

Dr Janusz R. Getta

School of Computing and Information Technology -
University of Wollongong

Data Warehouse Concepts

Outline

OLAP versus OLTP

Traditional database systems designed and tuned to support the day-to-day operation:

- Ensure fast, concurrent access to data
- Transaction processing and concurrency control
- Focus on online update data consistency
- Known as operational databases or online transaction processing (OLTP)

OLTP database characteristics:

- Detailed data
- Do not include historical data
- Highly normalized
- Poor performance on complex queries including joins an aggregation

Data analysis requires a new paradigm: online analytical processing (OLAP)

- Typical OLTP query: pending orders for a customer
- Typical OLAP query: total sales amount by a product and by a customer

OLAP versus OLTP

OLAP characteristics

- OLTP paradigm focused on transactions, OLAP focused on analytical queries
- Normalization not good for analytical queries, reconstructing data requires a high number of joins
- OLAP databases support a heavy query load
- OLTP indexing techniques not efficient in OLAP: oriented to access few records; OLAP queries typically include aggregation

The need for a different database model to support OLAP was clear: led to data warehouses

Data warehouse: (usually) large repositories that consolidate data from different sources (internal and external to the organization), are updated offline, follow the multidimensional data model, designed and optimized to efficiently support OLAP queries

Data Warehouse Concepts

Outline

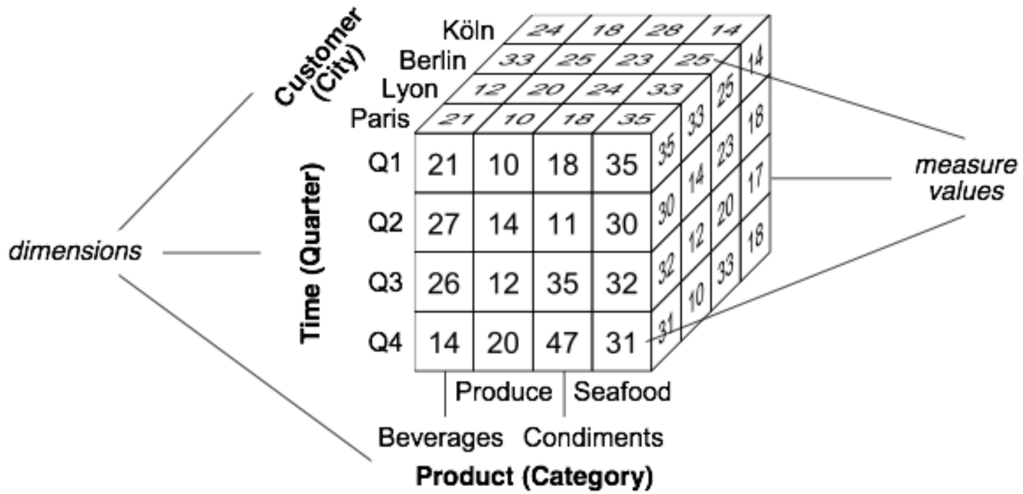
The Multidimensional Model

A view of data in n-dimensional space: a data cube

A data cube is composed of dimensions and facts

Dimensions: Perspectives used to analyze the data

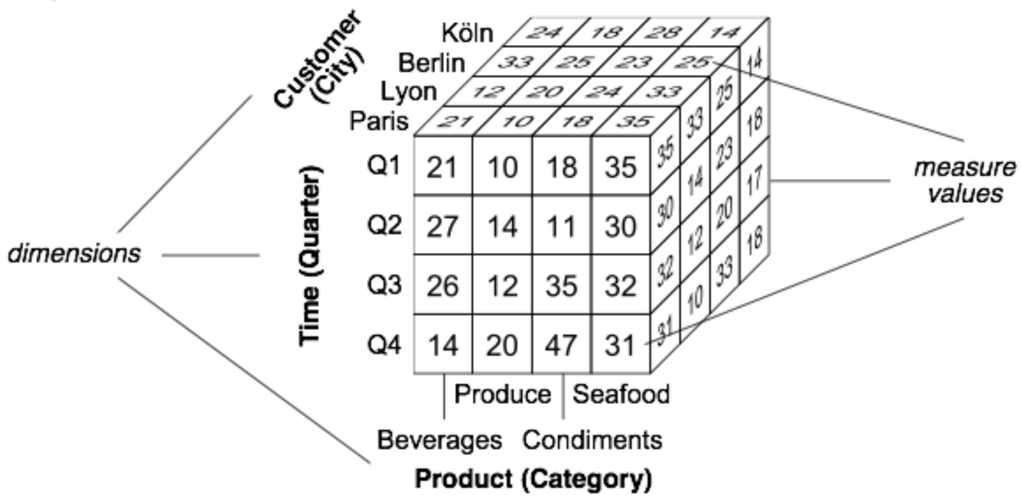
- Example: A three-dimensional cube for sales data with dimensions `Product`, `Time`, and `Customer`, and a measure `Quantity`



Attributes describe dimensions

- Product dimension may have attributes `ProductNumber` and `UnitPrice` (not shown in the figure)

The Multidimensional Model



The cells or facts of a data cube have associated numeric values called measures

Each cell of the data cube represents `Quantity` of units sold by `category`, `quarter`, and `customer's city`

Data granularity: level of detail at which measures are represented for each dimension of the cube

- Example: sales figures aggregated to granularities `Category`, `Quarter`, and `City`

The Multidimensional Model

Instances of a dimension are called members

- Example: `Seafood` and `Beverages` are members of the `Product` at the granularity `Category`

A data cube contains several measures, e.g. `Amount`, indicating the total sales amount (not shown)

A data cube may be sparse (typical case) or dense

- Example: not all customers may have ordered products of all categories during all quarters

Hierarchies: allow viewing data at several granularities

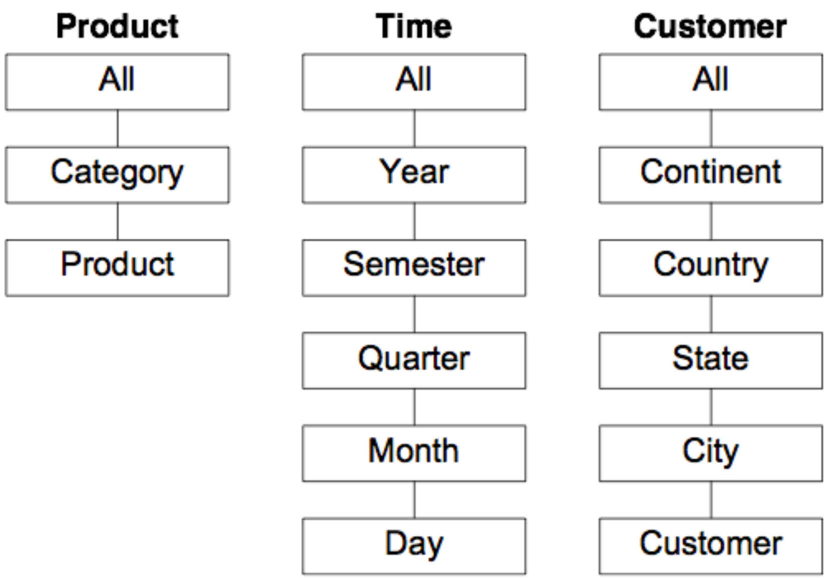
- Define a sequence of mappings relating lower-level, detailed concepts to higher-level ones
- The lower level is called the child and the higher level is called the parent
- The hierarchical structure of a dimension is called the dimension schema
- A dimension instance comprises all members at all levels in a dimension

The Multidimensional Model

In the previous figure, granularity of each dimension indicated between parentheses: Category for the `Product` dimension, `Quarter` for `Time`, and `City` for `Customer`

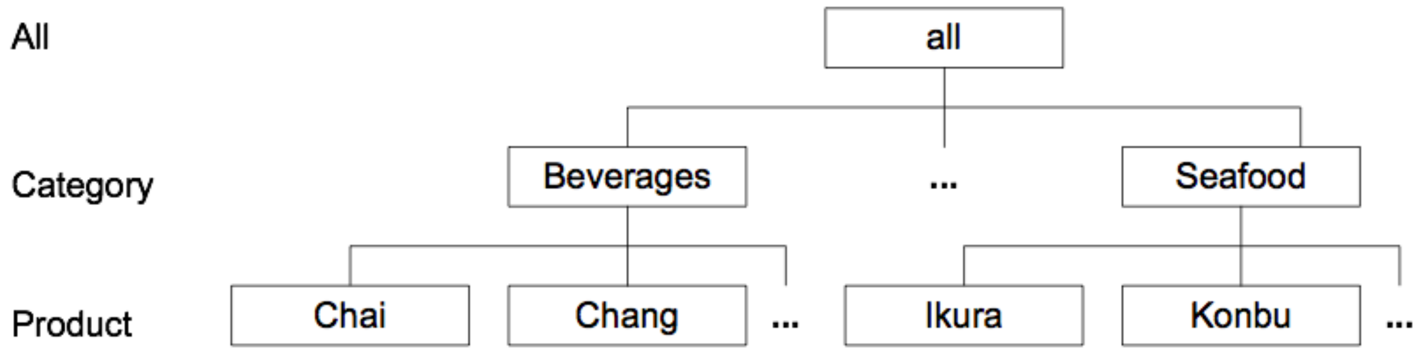
We may want sales figures at a finer granularity (`Month`), or at a coarser granularity (`Country`)

Hierarchies of the `Product`, `Time`, and `Customer` dimensions



The Multidimensional Model

Members of a hierarchy `Product` - `Category`



The Multidimensional Model: Measures

Aggregation of measures changes the abstraction level at which data in a cube are visualized

Measures can be:

- Additive: can be meaningfully summarized along all the dimensions, using addition; The most common type of measures
- Semiadditive: can be meaningfully summarized using addition along some dimensions; Example: inventory quantities, which cannot be added along the Time dimension
- Nonadditive measures cannot be meaningfully summarized using addition across any dimension; Example: item price, cost per unit, and exchange rate

The Multidimensional Model: Measures

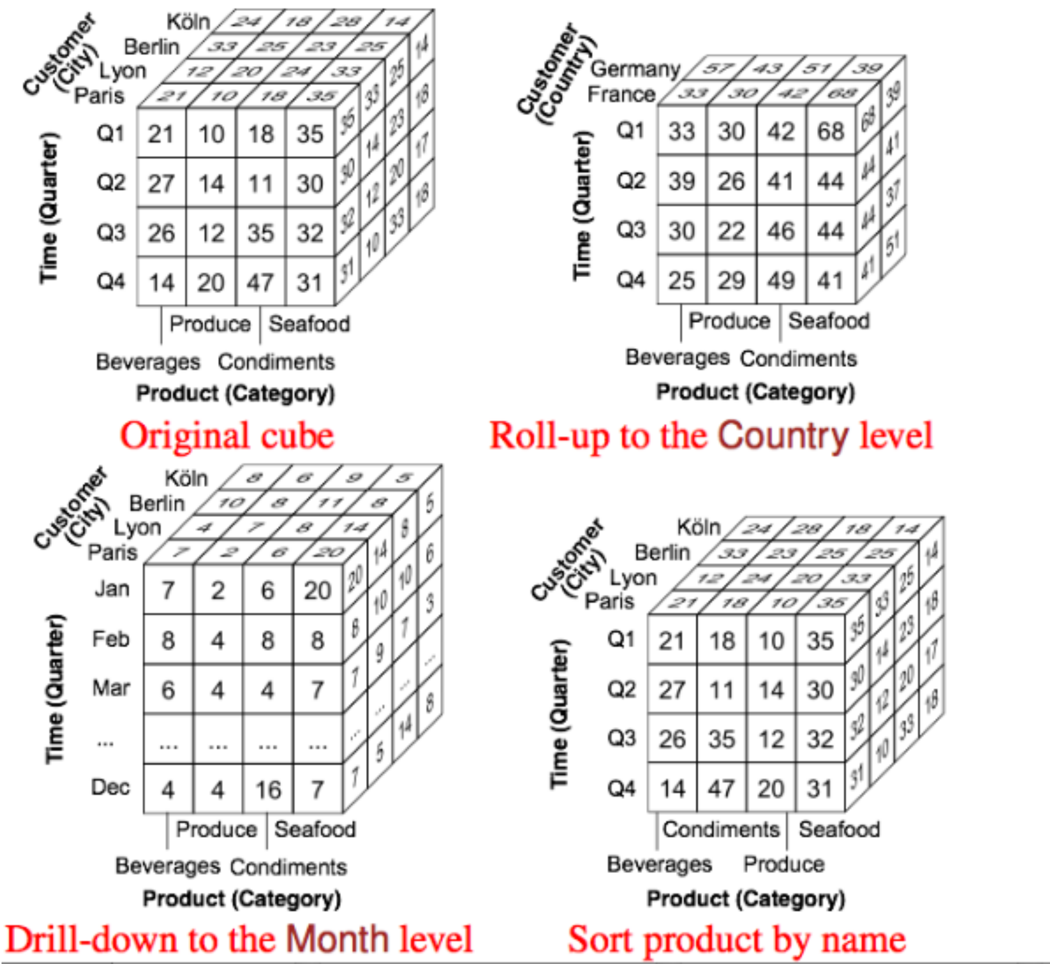
Another classification of measures:

- Distributive: defined by an aggregation function that can be computed in a distributed way; Functions `count`, `sum`, `minimum`, and `maximum` are distributive, `distinct count` is not; Example: S = {3, 3, 4, 5, 8, 4, 7, 3, 8} partitioned in subsets {3, 3, 4}, {5, 8, 4}, {7, 3, 8} gives a result of 8, while the answer over the original set is 5
- Algebraic measures are defined by an aggregation function that can be expressed as a scalar function of distributive ones; example: `average`, computed by dividing the sum by the count

Data Warehouse Concepts

Outline

OLAP Operations



OLAP Operations

Starting cube: quarterly sales (in thousands) by product category and customer cities for 2012

We first compute the sales quantities by country: a `roll-up` operation to the `Country` level along the `Customer` dimension

Sales of category Seafood in France significantly higher in the first quarter

- To find out if this occurred during a particular month, we take cube back to `City` aggregation level, and `drill-down` along `Time` to the `Month` level

To explore alternative visualizations, we `sort` products by name

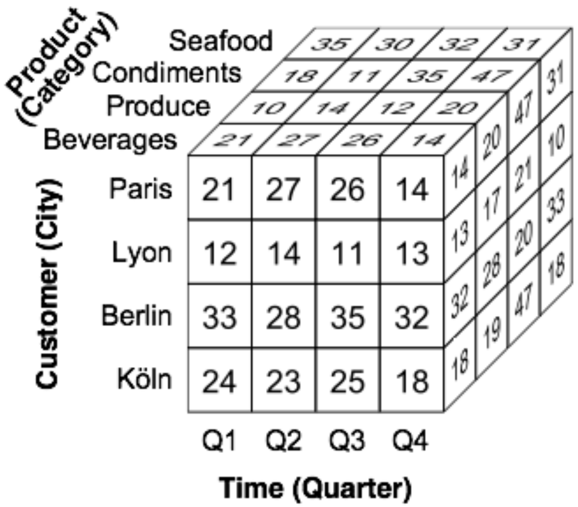
To see the cube with the `Time` dimension on the x axis, we rotate the axes of the original cube, without changing granularities → `pivoting` (see next 2 slides)

OLAP Operations

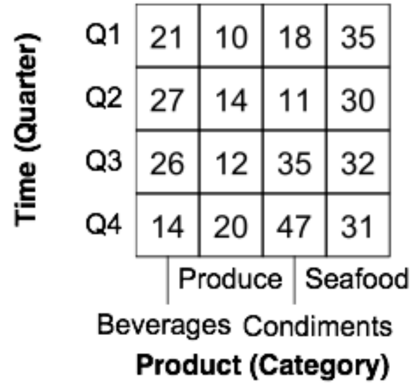
To visualize the data only for Paris → `slice` operation, results in a 2-dimensional sub-cube, basically a collection of time series (see next slide)

To obtain a 3-dimensional sub-cube containing only sales for the first two quarters and for the cities Lyon and Paris, we go back to the original cube and apply a `dice` operation

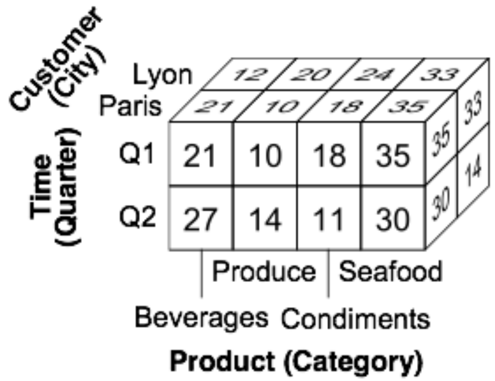
OLAP Operations



Pivot



Slice on City='Paris'



Dice on City='Paris' or 'Lyon' and Quarter='Q1' or 'Q2'

OLAP Operations

The operations in the previous slides can be defined using the following algebraic operators.

`Roll-up`: aggregates measures along a dimension hierarchy (using an aggregate function) to obtain measures at a coarser granularity

```
ROLLUP(CubeName, (Dimension → Level)∗, AggFunction(Measure)∗)
ROLLUP(Sales, Customer → Country, SUM(Quantity))
```
OLAP

Extended roll-up: similar to rollup, but drops all dimensions not involved in the operation

```
ROLLUP∗(CubeName, [(Dimension → Level)∗], AggFunction(Measure)∗)
ROLLUP∗(Sales, Time → Quarter, SUM(Quantity))
ROLLUP∗(Sales, Time → Quarter, COUNT(Product) AS ProdCount)
```
OLAP

Recursive roll-up: aggregates over a recursive hierarchy (a level rolls-up to itself)

```
RECROLLUP(CubeName, Dimension → Level, AggFunction(Measure)∗)
```
OLAP

OLAP Operations

`Drill-down` moves from a more general level to a more detailed level in a hierarchy

```
DRILLDOWN(CubeName, (Dimension → Level)*)
DRILLDOWN(Sales, Time → Month)
```
OLAP

`Sort` returns a cube where the members of a dimension have been sorted according to the value of Expression

```
SORT(CubeName, Dimension, Expression [ASC | DESC])
```
OLAP

```
SORT(Sales, Product, NAME)
```

- NAME is a predefined keyword in the algebra representing the name of a member

OLAP Operations

Pivot

```
PIVOT(CubeName, (Dimension → Axis)∗)
```
OLAP

- where the axes are specified as {X, Y, Z, X_1, Y_1, Z_1, ... }.

```
PIVOT(Sales, Time → X, Customer → Y, Product → Z)
```
OLAP

Slice:

```
SLICE(CubeName, Dimension, Level = Value)
```
OLAP

- Dimension will be dropped by fixing a single Value in the Level, other dimensions unchanged

```
SLICE(Sales, Customer, City = 'Paris')
```
OLAP

- Slice supposes that the granularity of the cube is at the specified level of the dimension

OLAP Operations

Dice:

```
DICE(CubeName, ? )                                                    OLAP
```

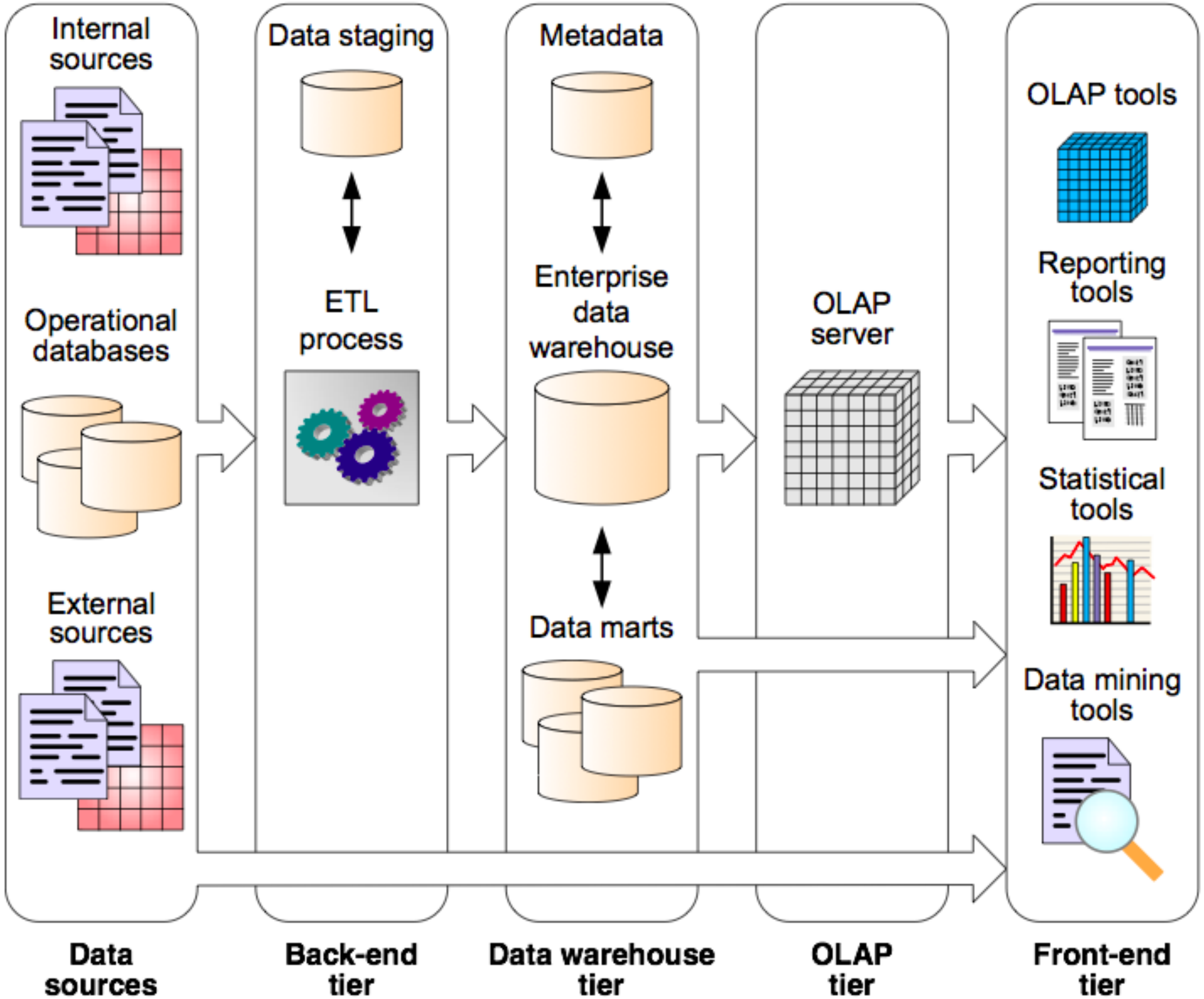
- where ? is a Boolean condition over dimension levels, attributes, and measures.

```
DICE(Sales, (Customer.City = 'Paris' OR Customer.City = 'Lyon') AND   OLAP
            (Time.Quarter = 'Q1' OR Time.Quarter = 'Q2') )
```

Data Warehouse Concepts

Outline

Typical Data Warehouse Architecture



Data Warehouse Architecture

General data warehouse architecture: several tiers

Back-end tier composed of:

- The extraction, transformation, and loading (ETL) tools: Feed data into the data warehouse from operational databases and internal and external data sources
- The data staging area: An intermediate database where all the data integration and transformation processes are run prior to the loading of the data into the data warehouse

Data warehouse tier composed of:

- An enterprise data warehouse and/or several data marts
- A metadata repository storing information about the data warehouse and its contents

OLAP tier composed of:

- An OLAP server which provides a multidimensional view of the data, regardless the actual way in which data are stored

Data Warehouse Architecture

Front-end tier is used for data analysis and visualization

- Contains client tools such as OLAP tools, reporting tools, statistical tools, and data-mining tools

References

A. VAISMAN, E. ZIMANYI, Data Warehouse Systems: Design and Implementation, Chapter 3 Data Warehouse Concepts, Springer Verlag, 2014