ISIT312 Big Data Management

# Data Warehouse Concepts

Dr Fenghui Ren

School of Computing and Information Technology -
University of Wollongong

# Data Warehouse Concepts

## Outline

- OLAP versus OLTP
- The Multidimensional Model
- OLAP Operations
- Data Warehouse Architecture

# 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

- OLAP versus OLTP
- The Multidimensional Model
- OLAP Operations
- Data Warehouse Architecture

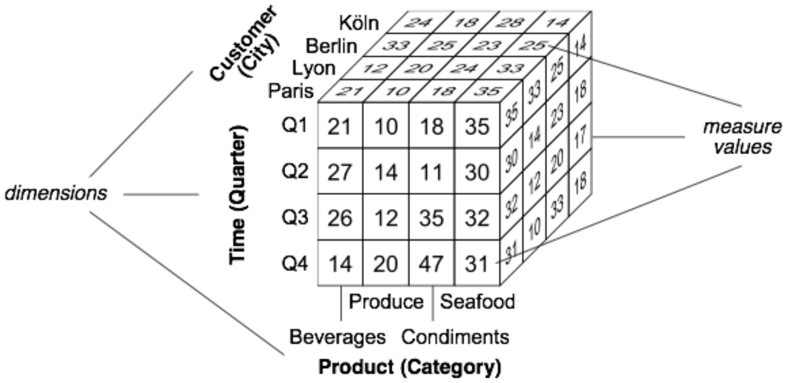
# The Multidimensional Model

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

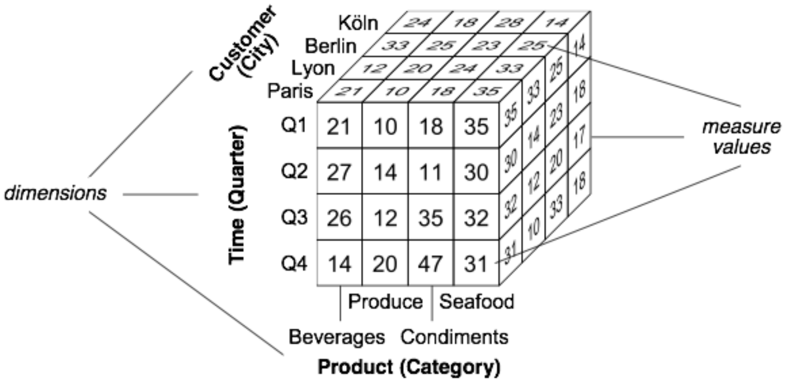
- Example: A three-dimensional cube for sales data with dimensions `Product`, `Time`, and `Customer`, and a measure `Quantity`



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

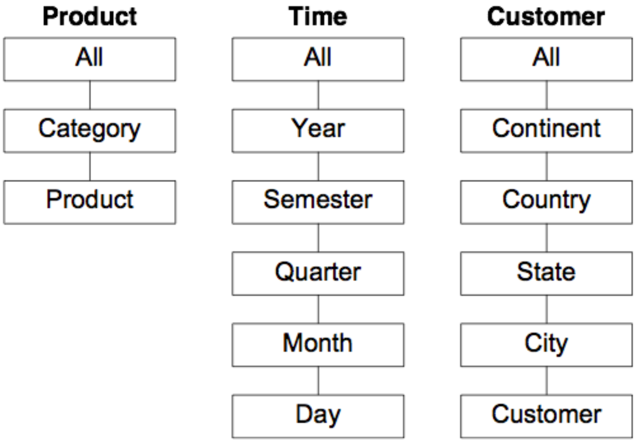
- Define a sequence of mappings relating lower-level, detailed concepts to higher-level ones
- The lower level is called the child and the higher level is called the parent
- The hierarchical structure of a dimension is called the dimension schema
- A dimension instance comprises all members at all levels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

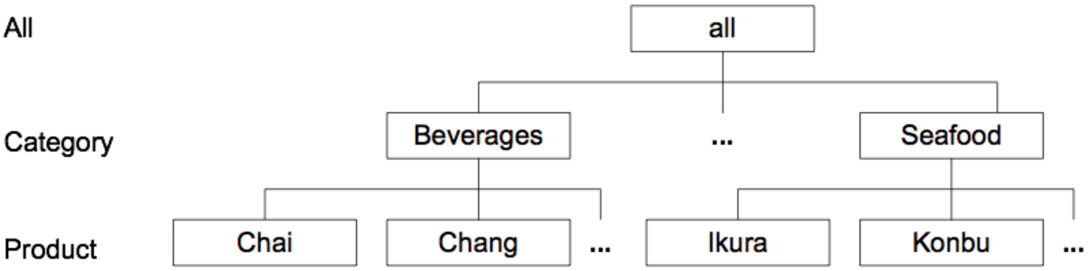
We may want sales figures at a finer granularity (`Month`), or at a coarser granularity (`Country`)

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:

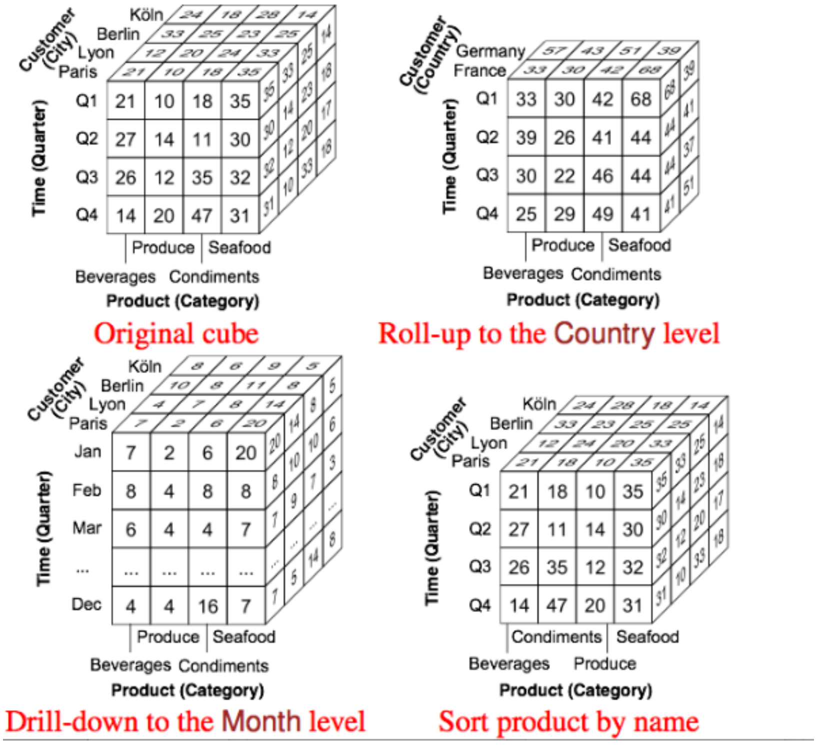
- Distributive: defined by an aggregation function that can be computed in a distributed way; Functions `count`, `sum`, `minimum`, and `maximum` are distributive, `distinct count` is not; Example: S = {3, 3, 4, 5, 8, 4, 7, 3, 8} partitioned in subsets {3, 3, 4}, {5, 8, 4}, {7, 3, 8} gives a result of 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 versus OLTP
- The Multidimensional Model
- OLAP Operations
- Data Warehouse Architecture

# OLAP Operations



| Time (Quarter) | Beverages | Produce | Condiments | Seafood |
|---|---|---|---|---|
| Q1 | 21 | 10 | 18 | 35 |
| Q2 | 27 | 14 | 11 | 30 |
| Q3 | 26 | 12 | 35 | 32 |
| Q4 | 14 | 20 | 47 | 31 |

Original cube

| Time (Quarter) | Beverages | Produce | Condiments | Seafood |
|---|---|---|---|---|
| Q1 | 33 | 30 | 42 | 68 |
| Q2 | 39 | 26 | 41 | 44 |
| Q3 | 30 | 22 | 46 | 44 |
| Q4 | 25 | 29 | 49 | 41 |

Roll-up to the Country level

| Time (Quarter) | Beverages | Produce | Condiments | Seafood |
|---|---|---|---|---|
| Jan | 7 | 2 | 6 | 20 |
| Feb | 8 | 4 | 8 | 8 |
| Mar | 6 | 4 | 4 | 7 |
| ... | ... | ... | ... | ... |
| Dec | 4 | 4 | 16 | 7 |

Drill-down to the Month level

| Time (Quarter) | Beverages | Condiments | Produce | Seafood |
|---|---|---|---|---|
| Q1 | 21 | 18 | 10 | 35 |
| Q2 | 27 | 11 | 14 | 30 |
| Q3 | 26 | 35 | 12 | 32 |
| Q4 | 14 | 47 | 20 | 31 |

Sort product by name

# 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

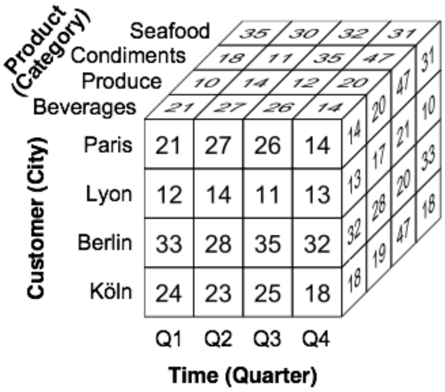
To see the cube with the `Time` dimension on the x axis, we rotate the axes of the original cube, without changing granularities → `pivoting` (see next 2 slides)

# 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)

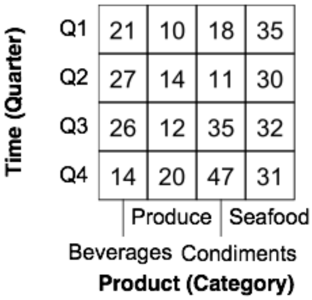
To obtain a 3-dimensional sub-cube containing only sales for the first two quarters and for the cities Lyon and Paris, we go back to the original cube and apply a `dice` operation

# OLAP Operations



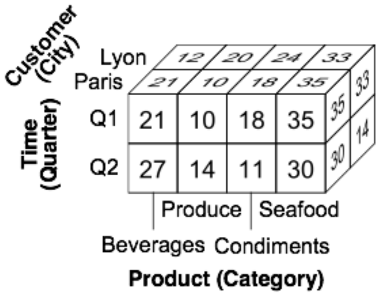
| | Q1 | Q2 | Q3 | Q4 |
|---|---|---|---|---|
| Paris | 21 | 27 | 26 | 14 |
| Lyon | 12 | 14 | 11 | 13 |
| Berlin | 33 | 28 | 35 | 32 |
| Köln | 24 | 23 | 25 | 18 |

Pivot


Time (Quarter)
Product (Category)

| | Beverages | Produce | Condiments | Seafood |
|---|---|---|---|---|
| Q1 | 21 | 10 | 18 | 35 |
| Q2 | 27 | 14 | 11 | 30 |
| Q3 | 26 | 12 | 35 | 32 |
| Q4 | 14 | 20 | 47 | 31 |

Slice on City=’Paris’



| | Beverages | Produce | Condiments | Seafood |
|---|---|---|---|---|
| Q1 | 21 | 10 | 18 | 35 |
| Q2 | 27 | 14 | 11 | 30 |

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

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

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

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

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

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

# OLAP Operations

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

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

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

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

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

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

# OLAP Operations

## Pivot

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

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

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

## Slice:

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

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

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

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

# OLAP Operations

## Dice:

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

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

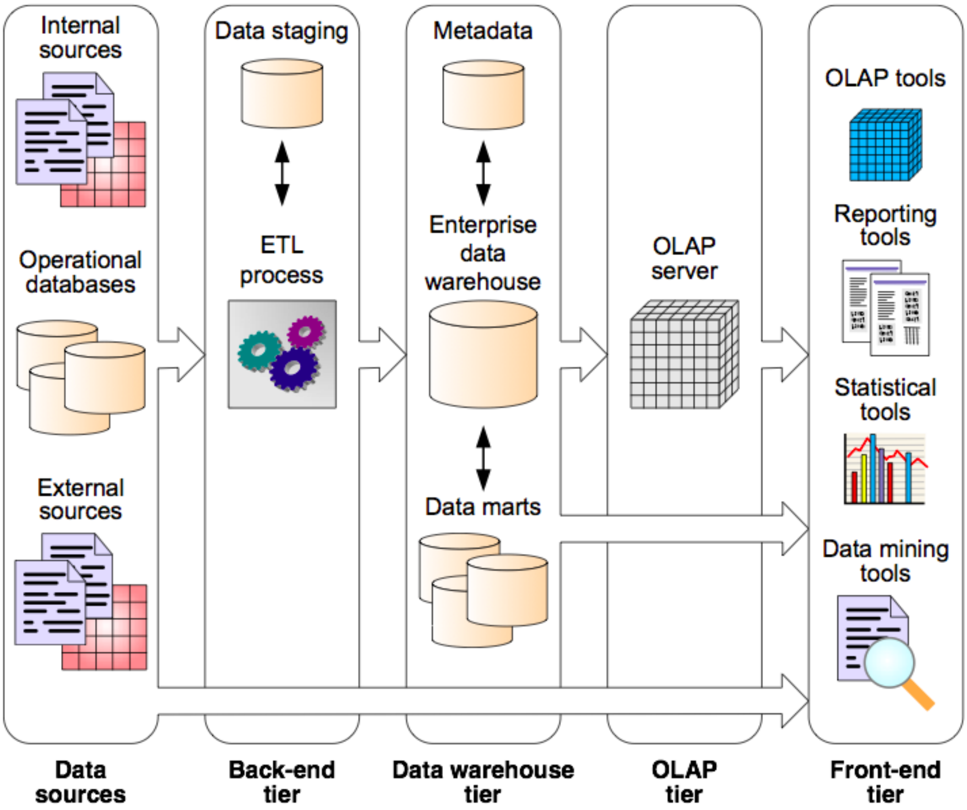
```OLAP
DICE(Sales, (Customer.City = 'Paris' OR Customer.City = 'Lyon') AND
            (Time.Quarter = 'Q1' OR Time.Quarter = 'Q2') )
```

# Data Warehouse Concepts

## Outline

- OLAP versus OLTP
- The Multidimensional Model
- OLAP Operations
- Data Warehouse Architecture

# 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