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Data Management for Big Data

Data Warehousing

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Outline

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Introduction

Introduction

Nowadays, most of large and medium size organizations are using information systems to implement their business processes.

As time goes by, these organizations produce a lot of data related to their business, but often these data are not integrated, been stored within one or more platforms.

Thus, they are hardly used for decision-making processes, though they could be a valuable aiding resource.

A central repository is needed; nevertheless, traditional databases are not designed to review, manage and store historical/strategic information, but deal with ever changing operational data, to support “daily transactions”.

What is Data Warehousing?

Data warehousing is a technique for collecting and managing data from different sources to provide meaningful business insights.

It is a blend of components and processes which allows the strategic use of data:

- Electronic storage of a large amount of information which is designed for query and analysis instead of transaction processing
- Process of transforming data into information and making it available to users in a timely manner to make a difference

Why Data Warehousing?

A normalized, relational database for an inventory system has many tables related to each other through foreign keys.

A report on monthly sales information may include many joined conditions.

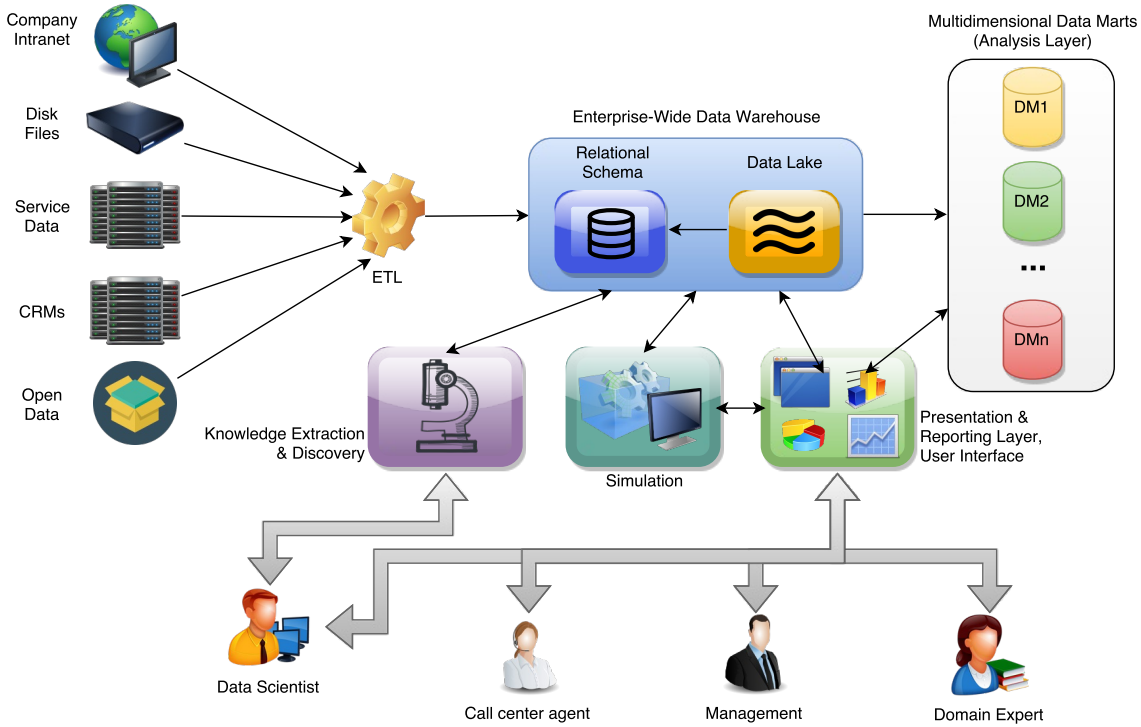
This can quickly slow down the response time of the query and report, especially with millions of records involved.

A data warehouse provides a new design which can help to reduce the response time and helps to enhance the performance of queries for reports and analytics.

Decision Support Systems

A data warehouse is typically the central component of a *Decision Support System*, i.e., an (descriptive / predictive / prescriptive) information system that supports business or organizational decision-making activities.

E.g., providing monitoring tools, graphs, reports, simulations.



Data Warehousing Fundamental Concepts

Data Warehouse

According to William Inmon, a data warehouse is a *subject-oriented, integrated, consistent, non-volatile, and time-variant collection of data* in support of management's decisions.

The analyst job in the data warehouse environment is easier than in the legacy environments:

- single integrated source of data
- granular data is easy (and fast) accessible
- data warehouse forms a foundation for reusability and reconciliation of data

The data warehouse is at the heart of the *decision support system* (DSS) operation.

Subject Oriented

The data warehouse focuses on enterprise-specific *concepts*, as defined in the high-level corporate data model. Subject areas may include:

- Customer
- Product
- Order
- Claim
- Account

Conversely, operational databases hang on enterprise-specific *applications*, meaning that data in them is typically organized by business processes, around the workflows of the company.

Integrated and Consistent

Data is fed from multiple, disparate sources into the data warehouse.

As the data is fed, it is converted, reformatted, resequenced, summarized, and so forth (ETL – Extract, Transform, Load).

Data is entered into the data warehouse in such a way that the many inconsistencies at the operational level are resolved.

Consistency applies to all application design issues, such as naming conventions, key structure, measurement of attributes, and physical characteristics of data.

Non-volatile

After the data is inserted in the warehouse it is neither changed nor removed.

The only exceptions happen when false data is inserted or the capacity of the data warehouse is exceeded and archiving becomes necessary.

This means that data warehouses can be essentially viewed as read-only databases.

When subsequent changes occur, a new snapshot record is written. In doing so, a historical record of data is kept in the data warehouse.

Time-variant

Time variancy implies that the warehouse stores data representative as it existed at many points in time in the past.

A time horizon is the length of time data is represented in an environment; a 5-to-10-year time horizon is normal for a data warehouse.

While operational databases contain current-value data, data warehouses contain sophisticated series of snapshots, each snapshot taken at a specific moment in time.

OLTP: On-Line Transaction Processing

OLTP queries are typical of operational, daily systems.

This kind of queries generally read or write a small number of tuples, executing transactions on detailed data.

A typical OLTP transaction in a banking environment may be the transfer of money from one account to another.

The four ACID properties (Atomicity, Consistency, Isolation, Durability) are essential for this kind of application, because otherwise money may for example get lost or doubled.

"On-line" means that the analyst should obtain a response in almost real time.

OLAP: On-Line Analytical Processing

On the contrary, the type of query generally executed in data warehouses is OLAP.

In OLAP applications the typical user is not interested in detailed data, but usually in aggregating data over large sets.

E.g., calculate the average amount of money that customers under the age of 20 withdrew from ATMs in a certain region.

OLAP data originates from data found at the operational level, but it is denormalized, summarized, and shaped by the requirements of the management (*multidimensional data*).

This typically requires complex and time consuming transactions to pre-process data.

OLAP queries do not change data warehouse content.

What is a Data Mart?

A data mart is focused on a single functional area of an organization and contains a subset of data stored in a Data Warehouse.

A data mart is a condensed version of Data Warehouse and is designed for use by a specific department, unit or set of users in an organization. E.g., Marketing, Sales, HR or finance. It is often controlled by a single department in an organization.

Data Mart usually draws data from only a few sources compared to a Data warehouse. Data marts are small in size and are more flexible compared to a Data Warehouse.

What is a Data Lake?

A Data Lake is a storage repository that can store large amounts of structured, semi-structured, and unstructured data.

- It is a place where to store every type of data in its native format with no fixed limits on size or type
- It allows to access data before the ETL process, thus it retains all data coming from the sources
- Data is only transformed when the user is about to use it (*schema on read*, vs. *schema on write* in the data warehouse)
- Storing information in a data lake is relatively inexpensive with respect to storing them in a data warehouse

Data Lake Caveats

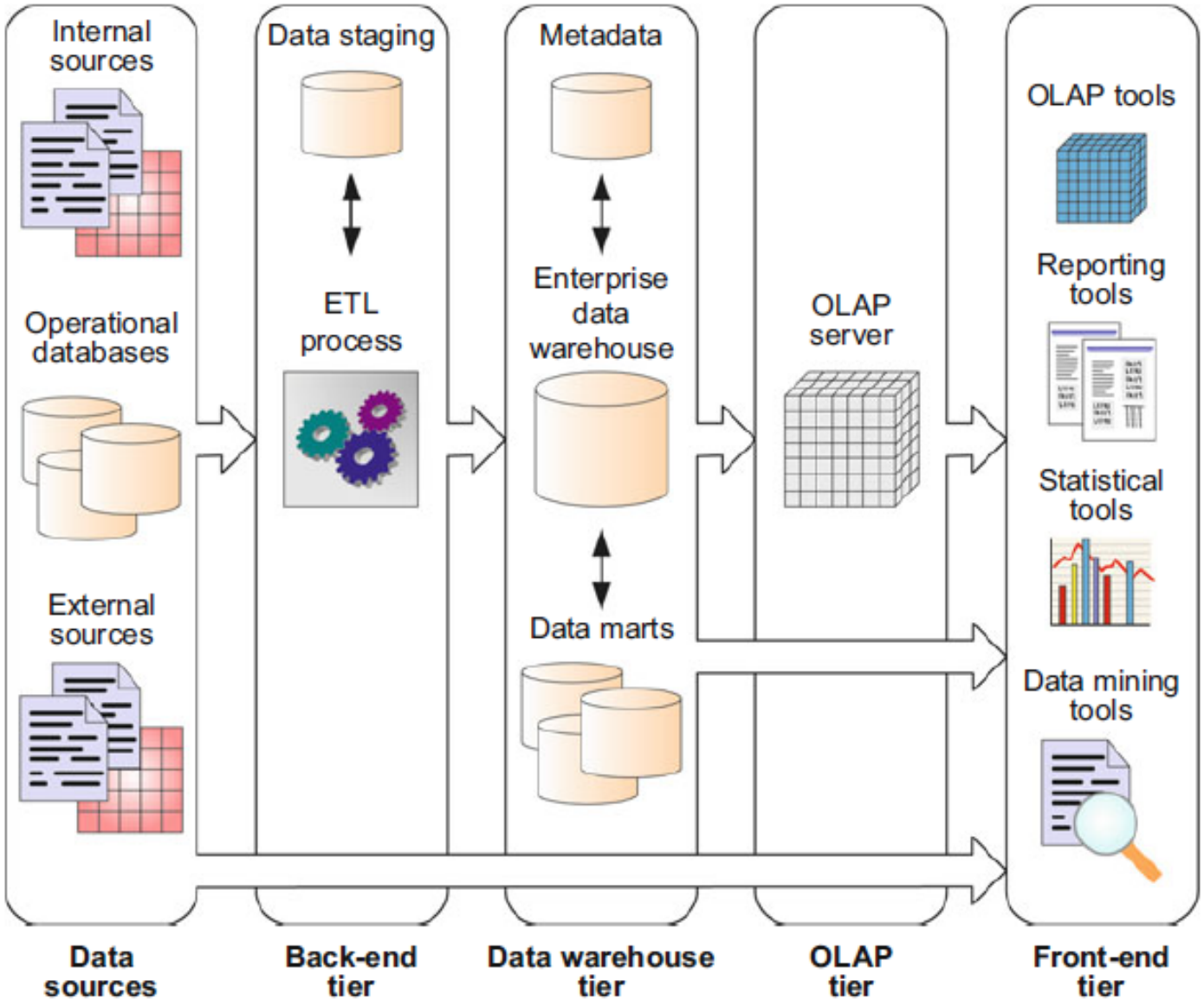
A Data Lake is not a substitute for a Data Warehouse.

For instance, a Data Warehouse guarantees quick answers for interactive queries thanks to the schema on write approach.

A Data Lake can grow without control and became useless (data swamp)...store only the possibly useful information!

Data Warehouse General Architecture

Data Warehouse Architecture Schema



Data Warehouse Architecture

A modern general data warehouse architecture typically consists of several tiers:

- *The back-end tier* includes extraction, transformation, and loading (ETL) tools and a data staging area
- *The data warehouse tier* is composed of an enterprise data warehouse and/or several data marts and a metadata repository (e.g., schema definitions, data lineage)
- *The OLAP tier* is composed of an OLAP server, which provides a multidimensional view of the data
- *The front-end tier* is used for data analysis and visualization. It contains client tools such as OLAP tools, reporting tools, statistical tools, and data mining tools

Extract, Transform, Load

The ETL process is in charge of loading data into the data warehouse, in bulk or as regular updates:

- *extract*: data is gathered from multiple, heterogenous sources
- *transform*: data cleansing (errors and inconsistencies removal), integration (data reconciliation, e.g., formats) and aggregation (to the level of granularity of the data warehouse)
- *load*: regularly feed the data warehouse the new data

Such operations are typically performed within a *data staging area*, i.e., an intermediate database.

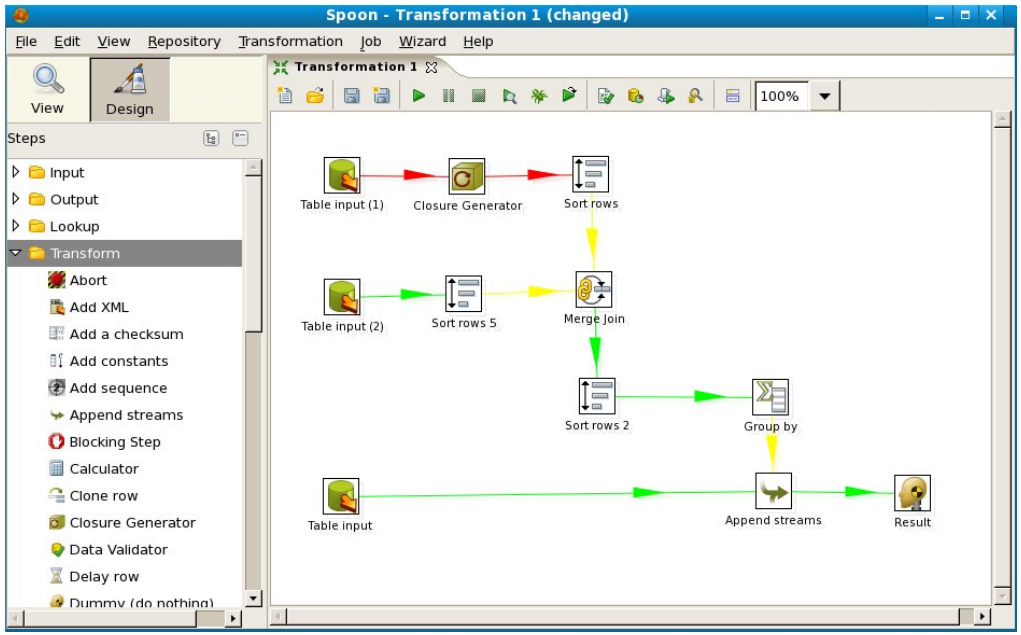
Always remember: *garbage in = garbage out*

ETL Tools

QuerySurge is built specifically to automate the testing of Data Warehouses & Big Data.

MarkLogic is a NoSQL data warehousing solution that includes a fully-fledged data integration and data management solution.

Pentaho Data Integration / Talend Open Studio support the creation of complex ETL workflows.



The Multidimensional Model

The Multidimensional Model

The distinctive features of OLAP applications suggest the adoption of a multidimensional representation of data, since running analytical queries against traditionally stored information would result in complex query specification and long response times.

The multidimensional model relies on the concepts of *fact*, *measure*, and *dimension*, and makes use of two kinds of tables: *fact tables* and *dimension tables*.

Facts and Measures

In a data warehouse context, a *fact* is the part of your data that indicates a specific event or transaction that has happened, like the sale of a product, or receiving a shipment.

A fact is composed of multiple numerical *measures*, that describe it.

As an example, a fact may be receiving an order for some shoes, detailed by the measures 'price'and 'quantity'.

Dimensions

A *dimension* can be thought of as a kind of structure that categorizes/indexes facts.

The primary functions of dimensions are threefold: to provide filtering, grouping and labelling to facts.

For instance, common dimensions may refer to: time, place, product.

Typically dimensions are organized internally into one or more hierarchies. For instance, *date* may have the hierarchy:

- Days (grouped into) Months (grouped into) Years

Example

Going back to our previous example, the order may be detailed by the following 2 *measures*, and 3 *dimension attributes*:

- total amount US$ 750
- quantity purchased is 10
- received yesterday at 2 pm
- served by our store in New York
- placed by customer #XAZ19

Fact Tables and Dimension Tables

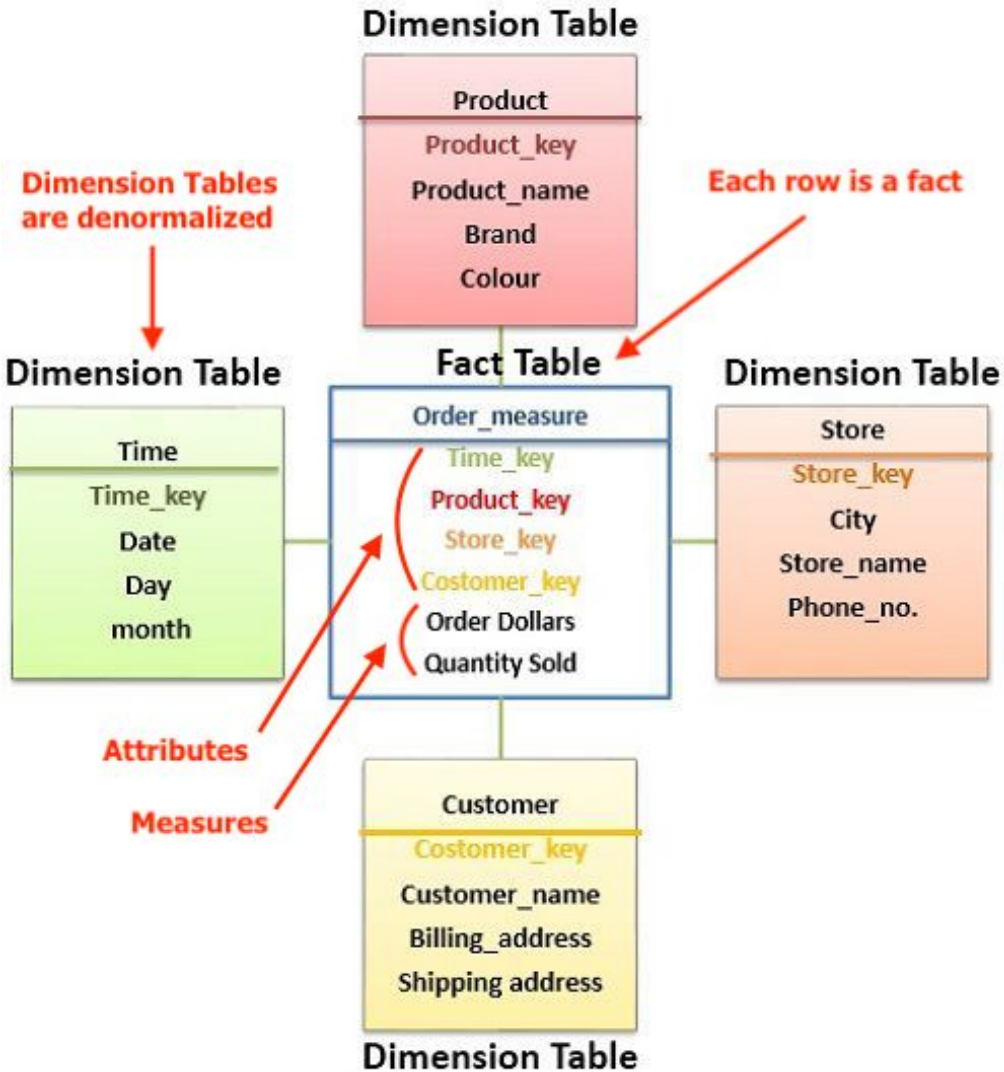
Fact Table:

- A fact table is a central table in a dimensional model
- It contains facts/measures and foreign keys to dimension tables

Dimension Table:

- A dimension table contains the dimensions of a fact
- There is no limit on the number of dimensions
- The dimension can also contain one or more hierarchical relationships

Example (Star Schema)



Operations over Multidimensional Data

The Multidimensional Model

In the multidimensional model, data is represented in an n-dimensional space, usually called a data cube or a hypercube.

A data cube is defined by dimensions (cube edges) and facts (cube cells):

- Dimensions are perspectives used to analyze the data (their hierarchies represent the granularity/level of detail)
- Facts have related numeric values (although we will see later that this is not always the case), called measures

Data cubes can be sparse: there may not be a cell value for each combination of dimensions.

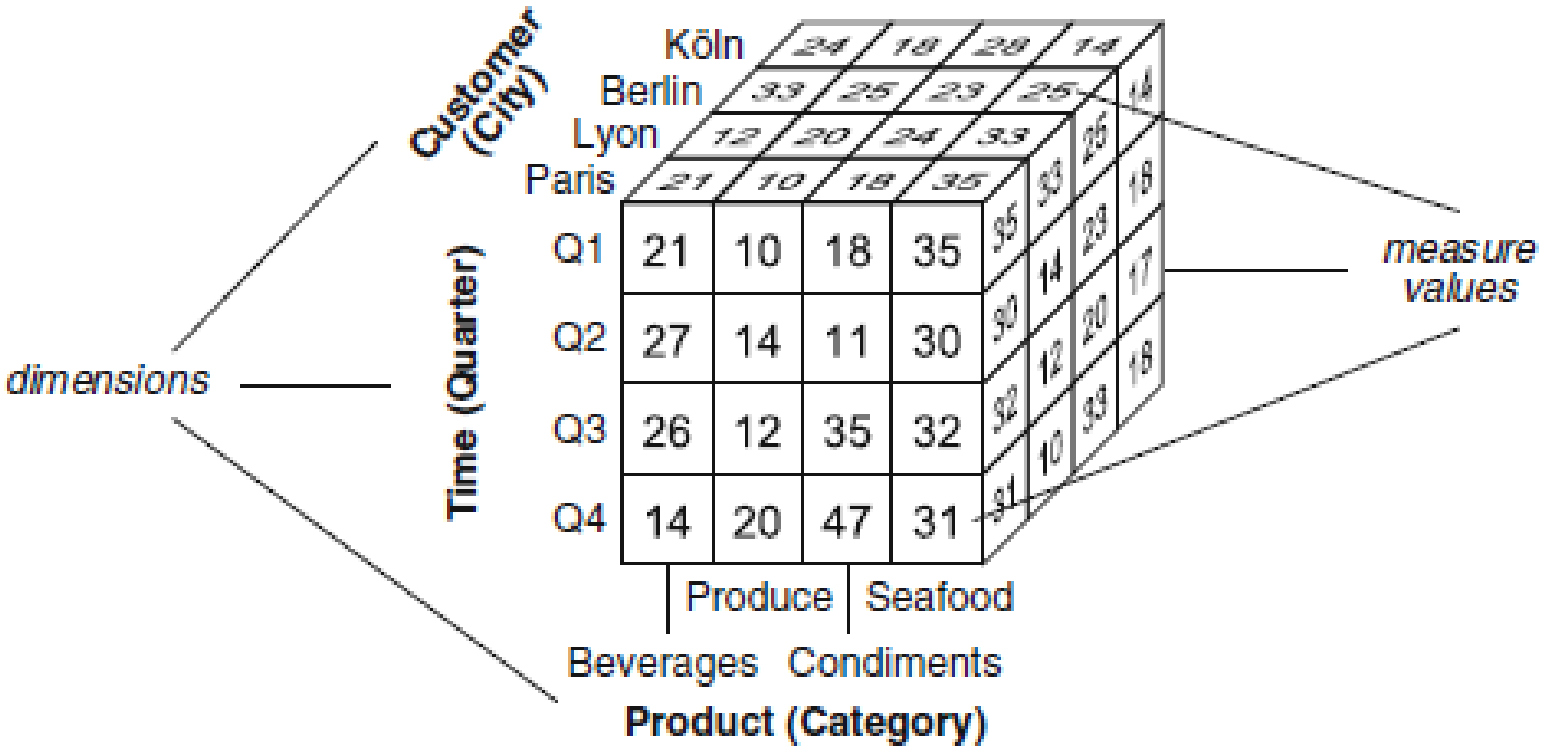
Multimensional Data in a Spreadsheet

Bi-dimensional pivot table, considering:

- measure 'Amount'
- dimensions 'Place'and 'Product'
- facts are the amount of products sold in each country

	A	B	C	D	E	F	G	H	I	J
1	Category	(All)								
2										
3	**Sum of Amount**	**Column**								
4	**Row Labels**	**Apple**	**Banana**	**Beans**	**Broccoli**	**Carrots**	**Mango**	**Orange**	**Grand Total**	
5	Australia	20634	52721	14433	17953	8106	9186	8680	131713	
6	Canada	24867	33775		12407		3767	19929	94745	
7	France	80193	36094	680	5341	9104	7388	2256	141056	
8	Germany	9082	39686	29905	37197	21636	8775	8887	155168	
9	New Zealand	10332	40050		4390			12010	66782	
10	United Kingdom	17534	42908	5100	38436	41815	5600	21744	173137	
11	United States	28615	95061	7163	26715	56284	22363	30932	267133	
12	**Grand Total**	**191257**	**340295**	**57281**	**142439**	**136945**	**57079**	**104438**	**1029734**	
13										

OLAP Cube Example



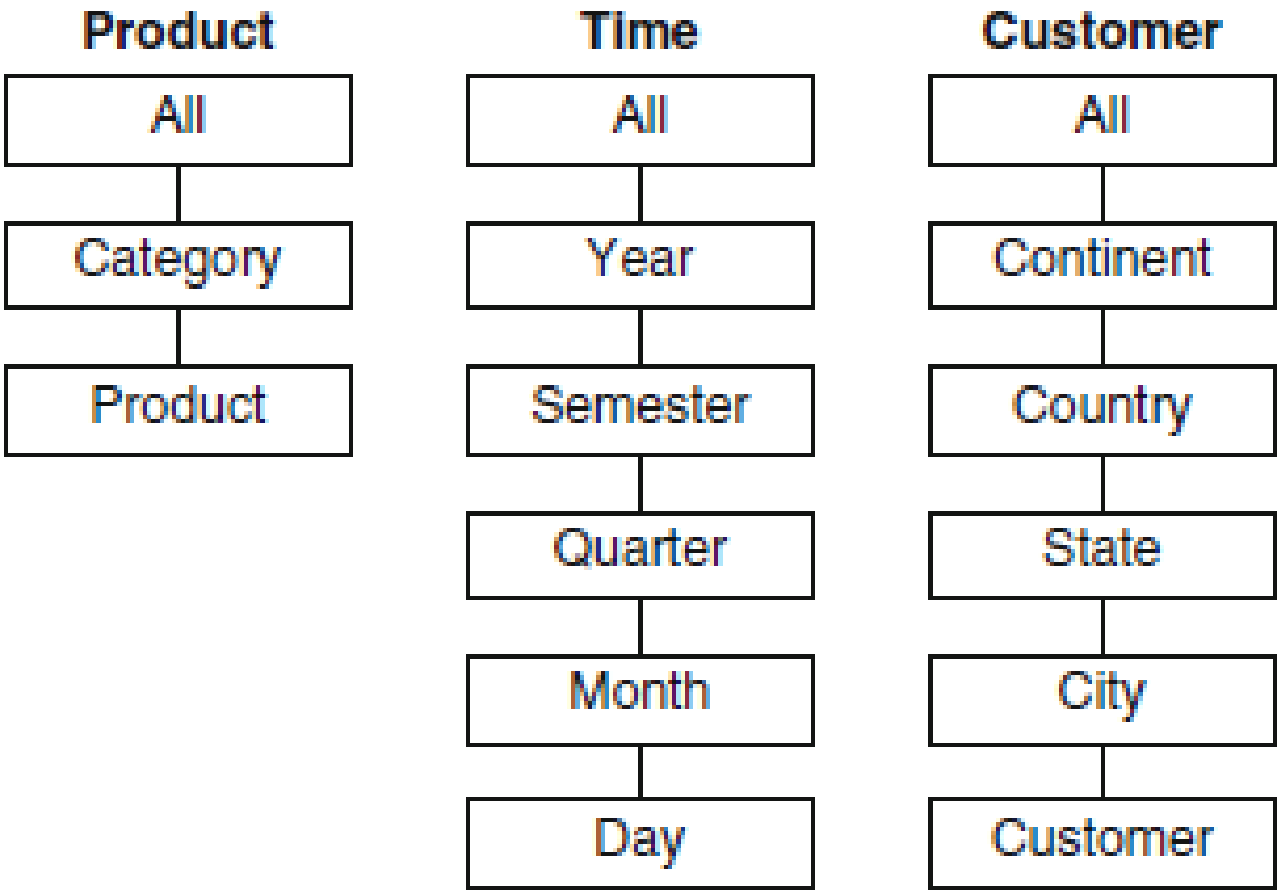
Dimension Hierarchies

To extract strategic knowledge from a cube, it is necessary to view its data at several levels of detail.

Dimension hierarchies allow to define a sequence of mappings relating lower-level, detailed concepts to higher-level, more general concepts.

As an example, dates of purchase could be aggregated into coarser grained levels of detail, such as months, or years.

Hierarchy Example



Aggregation of Measures

Each measure in a cube is associated with an aggregation function that combines several measure values into a single one.

Aggregation of measures takes place when one changes the level of detail at which data in a cube are visualized.

This is performed by traversing the hierarchies of the dimensions (e.g,. from monthly to yearly sales).

Pay attention to the aggregation functions that you apply to each measure while navigating the hierarchies (e.g., mind the difference between *sum* and *count*).

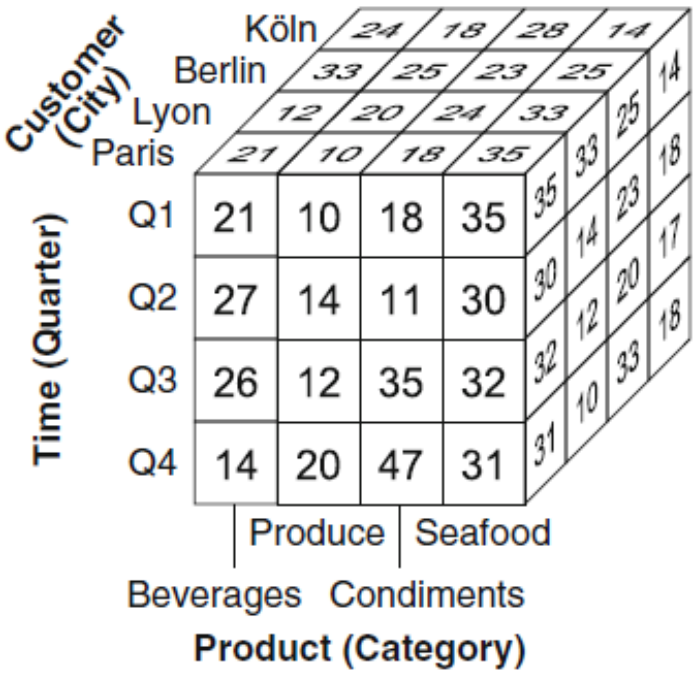
OLAP operations

The four types of analytical operations performed on OLAP cubes are:

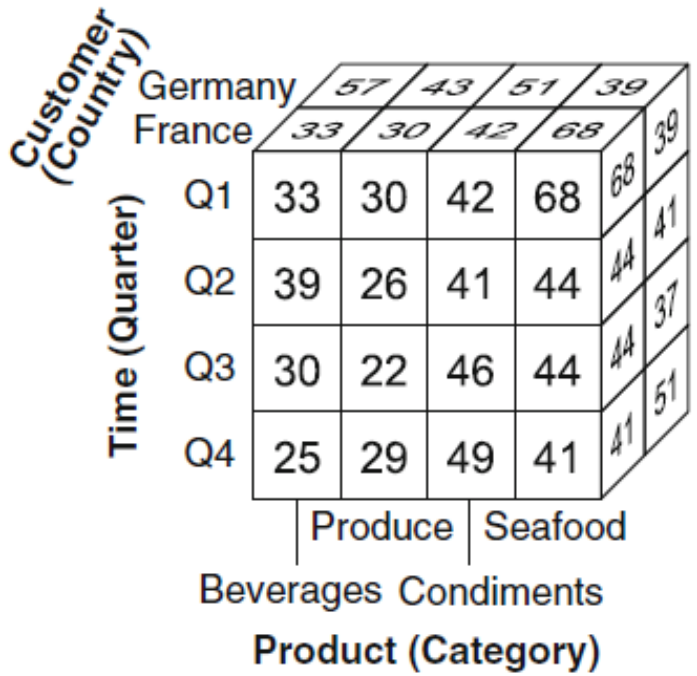
- Roll-up
- Drill-down
- Pivot (rotate)
- Slice and dice

Roll-up

It involves summarizing the data along a chosen dimension, navigating from a finer level of detail (down) to a coarser one (up).



(a) Original

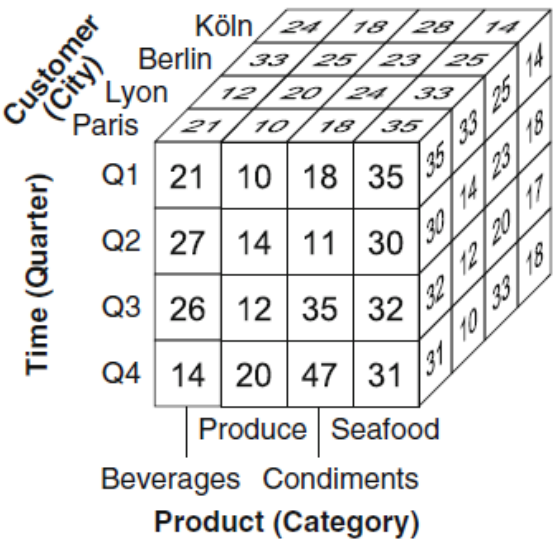


(b) Roll-up to the Country level

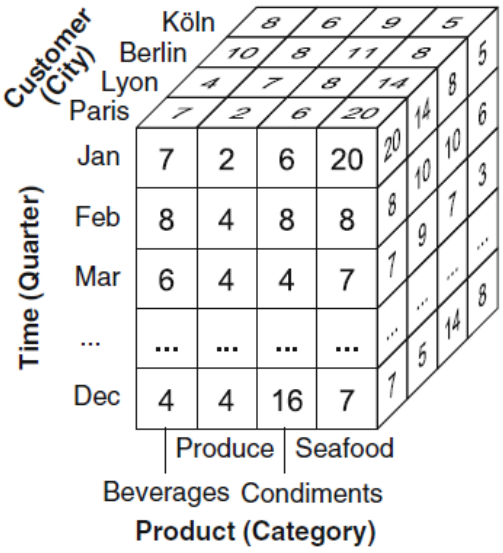
Drill-down

It allows the user to navigate among levels of data, ranging from the most summarized (up) to the most detailed (down), along a given hierarchy.

Looking at the detail beneath a summary number may be useful, especially where the summary number is surprising.



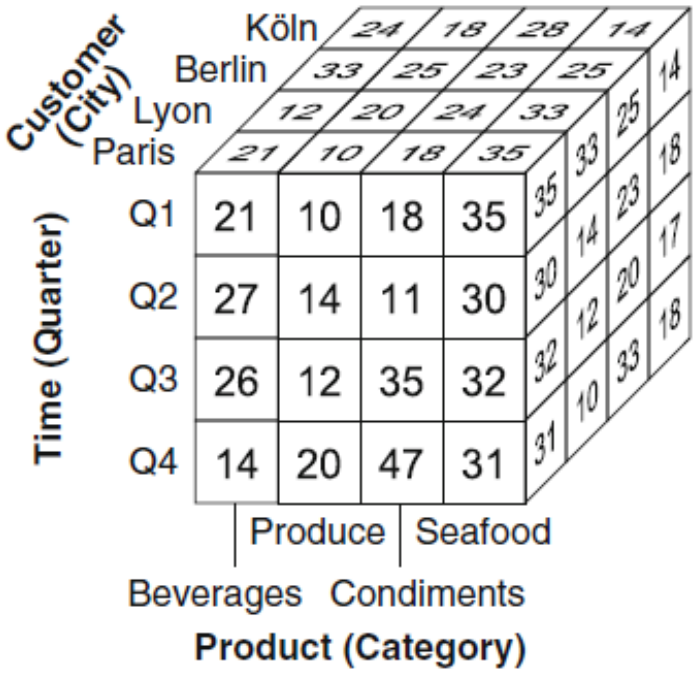
(c) Original



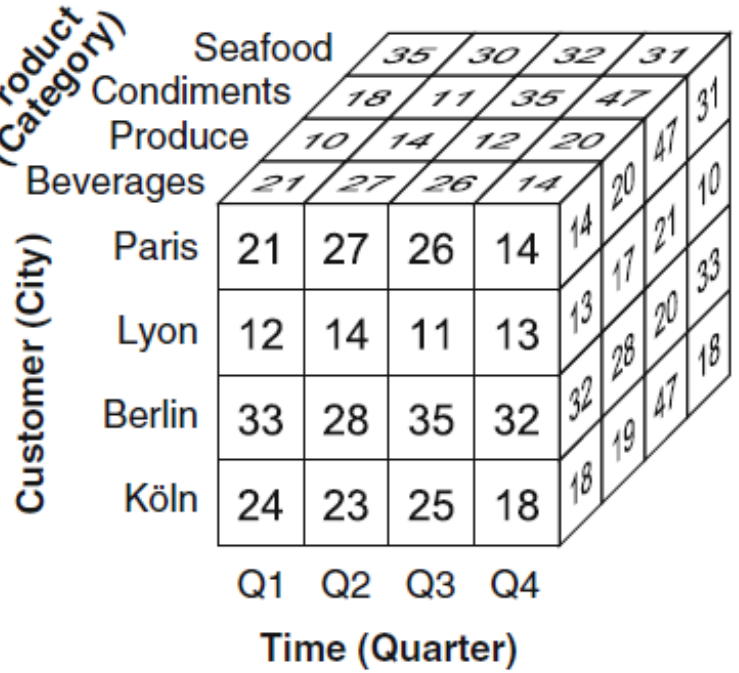
(d) Drill-down to the Month level

Pivot

This operation allows an analyst to rotate the cube in space to see its various faces.



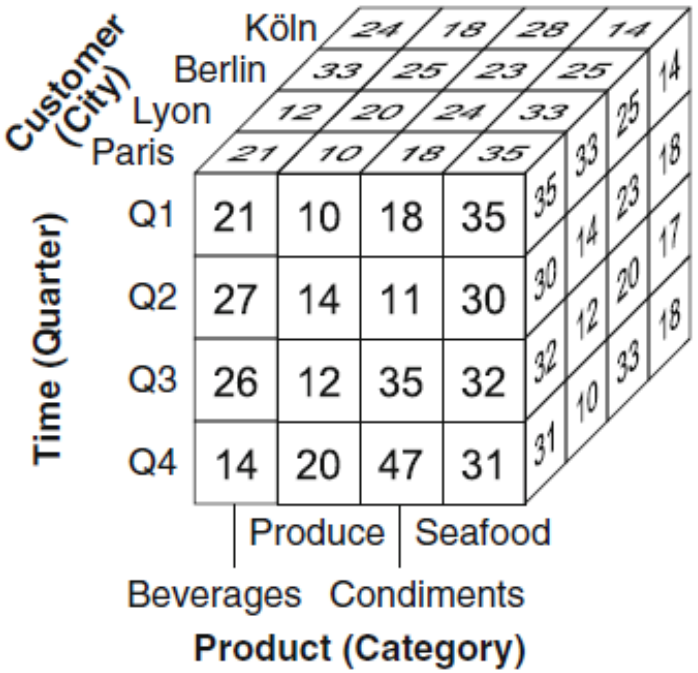
(e) Original



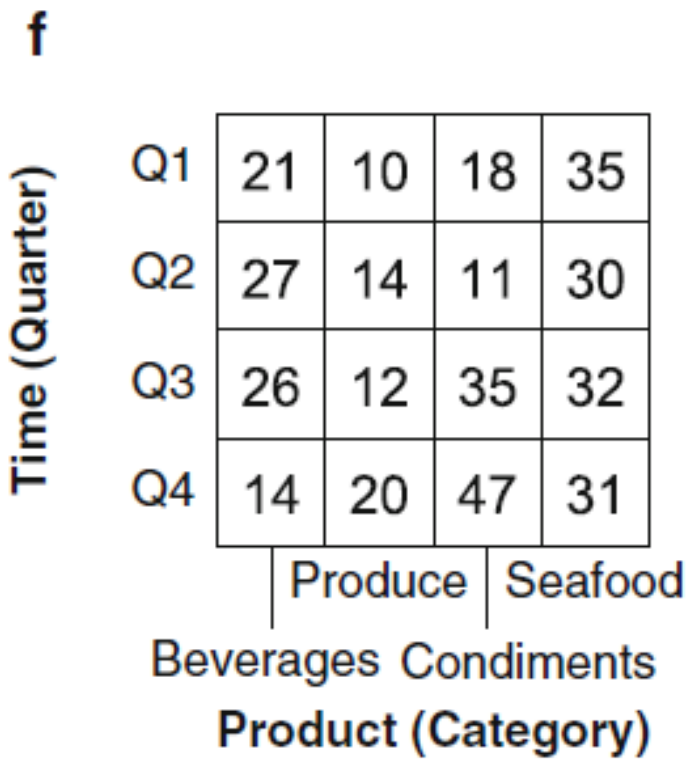
(f) Pivot to show Customer vs. Time

Slice

It is the act of picking a rectangular subset of a cube by choosing a single value for one of its dimensions, obtaining a new cube with one fewer dimension.



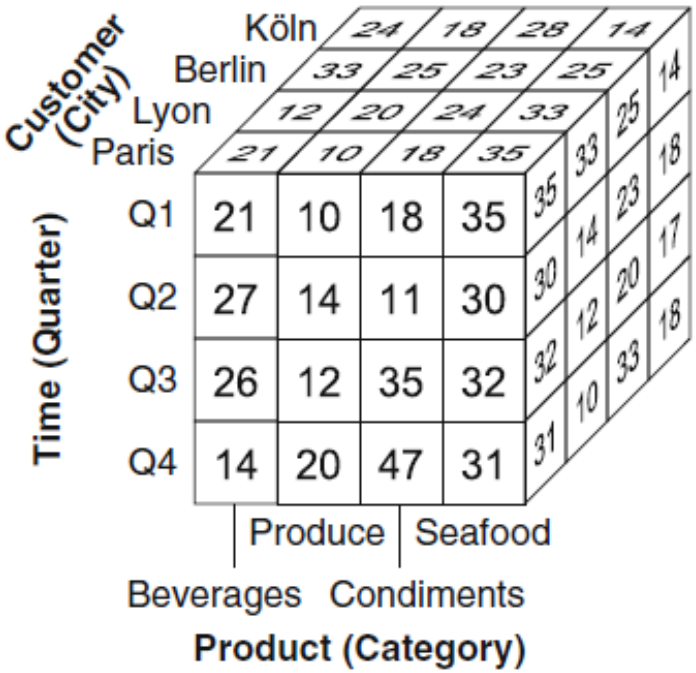
(g) Original



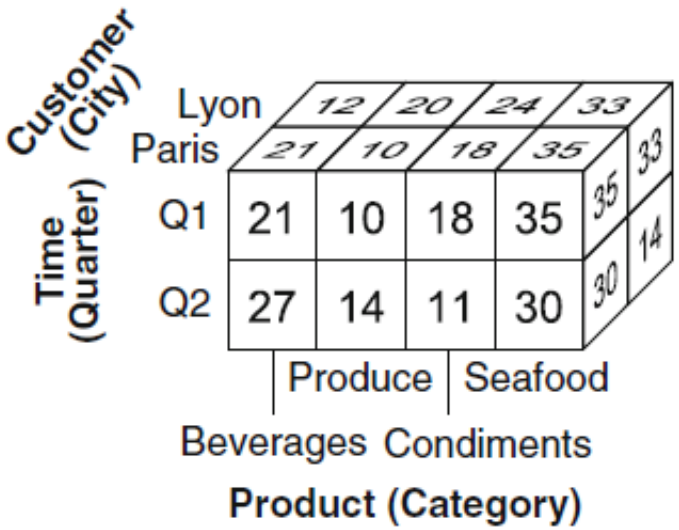
(h) Slice on City='Paris'

Dice

The dice operation is a generalization of slice. More than one dimension can be tested, with multiple conditions.



(i) Original



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

Implementing OLAP

- Extensive usage of materialized views
- Precomputing all the possible aggregations is space and time expensive
- 2^n GROUP BY combination for n dimensions
- It is better to precompute only some aggregated functions and derive the others exploiting the previous ones
- For instance sums wrt (item_name; color) can be obtained from (item_name; color; size)
- However, this is not possible in some cases (e.g., median)

Software for DW

- Talend, open source, www.talend.com (ETL)
- Kettle Pentaho, o.s., kettle.pentaho.com (ETL)
- Pentaho Business Analytics, www.pentaho.com
- Weka, o.s., www.cs.waikato.ac.nz/ml/weka (Data mining)
- RapidMiner, o.s., www.rapidminer.com (ETL, data mining)
- Mondrian, o.s., mondrian.pentaho.com (OLAP)
- Palo, o.s., sourceforge.net/projects/palo (MOLAP)
- jPivot, o.s., jpivot.sourceforge.net (client per Mondrian)
- Jasper, o.s., jasperforge.org (ETL, OLAP, . . .)
- Wabit, o.s., code.google.com/p/wabit (OLAP)

Software for DW (continued)

- Teradata, www.teradata.com (row/column store)
- Greenplum, www.greenplum.com (row/column store)
- HP Vertica, vertica.com (column store)
- Aster Data, www.asterdata.com (DBMS, map/reduce, R)
- Oracle BI, Essbase, . . . , oracle.com (vari prodotti)
- Sybase IQ, www.sybase.com/products (column store)
- IBM DB2, www.ibm.com/software/data/db2
- IBM Netezza, www.netezza.com
- IBM Cognos, www.ibm.com/software/analytics/
- HP Vertica, vertica.com (column store)
- LucidDB, o.s., www.luciddb.org (column store)
- MonetDB, o.s., www.monetdb.org (column store)
- SciDB, o.s., www.scidb.org

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