Business Intelligence Applications for Data Analysis

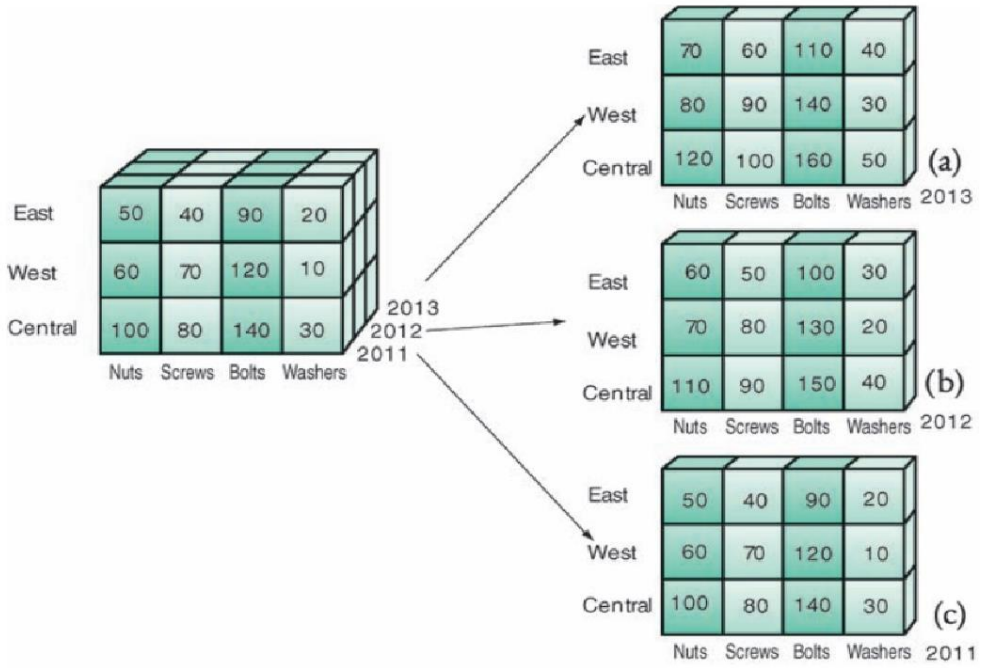
A good strategy to study the ways in which organizations use business intelligence applications is to consider how the users analyze data, how they present the results of their analyses, and how managers and executives (who can also be users) implement these results.

The data are stored in a data warehouse or data mart. The user community analyzes these data employing a variety of BI applications. The results of these analyses can be presented to users via other BI applications. Finally, managers and executives put the overall results to good use. You will become familiar with data analysis, data presentation, and data use in the next three sections. A variety of BI applications for analyzing data are available. They include multidimensional analysis (also called online analytical processing, or OLAP), data mining, and decision support systems

Multidimensional Analysis or Online Analytical Processing (OLAP)

Some BI applications include online analytical processing (OLAP), also referred to as multidimensional analysis capabilities. OLAP involves "slicing and dicing" data stored in a dimensional format, drilling down in the data to greater detail, and aggregating the data.

Data cube.



- Fig showing the data cube. The product is on the x-axis, geography is on the y-axis, and time is on the z-axis. Now, suppose you want to know how many nuts the company sold in the West region in 2009. You would slice and dice the cube, using nuts as the specific measure for product, West as the measure for

geography, and 2009 as the measure for time. The value or values that remain in the cell(s) after our slicing and dicing is (are) the answer to our question. As an example of drilling down, you also might want to know how many nuts were sold in January 2009. Alternatively, you might want to know how many nuts were sold during 2008–2010, which is an example of aggregation, also called "rollup.

- **Data Mining**

Data mining refers to the process of searching for valuable business information in a large database, data warehouse, or data mart.
Data mining can perform two basic operations:
(1) predicting trends and behaviors, and
(2) identifying previously unknown patterns. BI applications typically provide users with a view of what has happened; data mining helps to explain why it is happening, and it predicts what will happen in the future. Regarding the first operation, data mining automates the process of finding predictive information in large databases. Questions that traditionally required extensive hands-on analysis now can be answered directly and quickly from the data.
For example, targeted marketing relies on predictive information. Data mining can use data from past promotional mailings to identify those prospects who are most likely to respond favorably to future mailings. Another business problem that uses predictive information is the forecasting of bankruptcy and other forms of default. Data mining can also identify previously hidden patterns in a single step. For example, it can analyze retail sales data to discover seemingly unrelated products that people often purchase together. The classic example is beer and diapers. Data mining found that young men tend to buy beer and diapers at the same time when shopping at convenience stores.
One significant pattern-discovery operation is detecting fraudulent credit card transactions. As you use your credit card, a pattern emerges over time of the typical ways you use your card and your typical shopping behaviors—the places in which you use your card, the amounts you spend, and so on. If your card is stolen and used fraudulently, the usage often varies noticeably from your established pattern. Data mining tools can discern this difference and bring the issue to your attention. Numerous data mining applications are used in business and in other fields.
According to a Gartner report (www.gartner.com), most Fortune 1000 companies worldwide currently use data mining, as the following representative

examples illustrate. Note that in most cases the purpose of data mining is to identify a business opportunity to create a sustainable competitive advantage

- Retailing and sales. Predicting sales, preventing theft and fraud, and determining correct inventory levels and distribution schedules among outlets. For example, retailers such as AAFES (stores on military bases) use Fraud Watch from SAP (www.sap.com) to combat fraud by employees in their 1,400 stores
- Banking. Forecasting levels of bad loans and fraudulent credit card use, predicting credit card spending by new customers, and determining which kinds of customers will best respond to (and qualify for) new loan offers.
- Manufacturing and production. Predicting machinery failures, and finding key factors that help optimize manufacturing capacity.
- Insurance. Forecasting claim amounts and medical coverage costs, classifying the most important elements that affect medical coverage, and predicting which customers will buy new insurance policies.
- Policework. Tracking crime patterns, locations, and criminal behavior; identifying attributes to assist in solving criminal cases
- Healthcare. Correlating demographics of patients with critical illnesses, and developing better insights on how to identify and treat symptoms and their causes.
- Marketing. Classifying customer demographics that can be used to predict which customers will respond to a mailing or buy a particular product

Decision Support Systems

Decision support systems (DSSs) combine models and data in an attempt to analyze semistructured problems and some unstructured problems that involve extensive user involvement. Models are simplified representations, or abstractions, of reality. DSSs enable business managers and analysts to access data interactively, to manipulate these data, and to conduct appropriate analyses.

Decision support systems can enhance learning and contribute to all levels of decision making. DSSs also employ mathematical models. Finally, they have the related capabilities of sensitivity analysis, what-if analysis, and goal-seeking analysis, which you will learn about next. You should keep in mind that these three types of analysis are useful for any type of decision support application.

Excel, for example, supports all three. Sensitivity Analysis. Sensitivity analysis is the study of the impact that changes in one or more parts of a decision-making model have on other parts. Most sensitivity analyses examine the impact that changes in input variables have on output variables.

Most models include two types of input variables: decision variables and environmental variables. "What is our reorder point for these raw materials?" is a decision variable (internal to the organization). "What will the rate of inflation be?" is an environmental variable (external to the organization). The output in this example is the total cost of raw materials.

Companies generally perform a sensitivity analysis to determine the impact of environmental variables on the result of the analysis. Sensitivity analysis is extremely valuable because it enables the system to adapt to changing conditions and to the varying requirements of different decision-making situations. It provides a better understanding of the model as well as of the problem that the model purports to describe.

What-if Analysis.

A model builder must make predictions and assumptions regarding the input data, many of which are based on the assessment of uncertain futures. The results depend on the accuracy of these assumptions, which can be highly subjective. What-if analysis attempts to predict the impact of a change in the assumptions (input data) on the proposed solution.

For example, what will happen to the total inventory cost if the originally assumed cost of carrying inventories is 12 percent rather than 10 percent? In a well-designed BI system, managers themselves can interactively ask the computer these types of questions as often as they need to. Goal-Seeking Analysis.

Goal-seeking analysis represents a "backward" solution approach. It attempts to

calculate the value of the inputs necessary to achieve a desired level of output. For example, let's say that an initial BI analysis predicted a profit of $2 million. Management might want to know what sales volume would be necessary to generate a profit of $3 million. To find out, they would perform a goal-seeking analysis. The managers, however, cannot simply press a button labeled "increase sales." Instead, the company will need to take certain actions to bring about the sales increase. Options include lowering prices, increasing funding for research and development, paying the sales force a higher commission rate, enhancing the advertising program, and, of course, implementing some combination of these actions. Whatever the action is, it will cost money, and the goalseeking analysis must take this into account.