Adaptive Business Intelligence

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INTRODUCTION

Since the computer age dawned on mankind, one of the most important areas in information technology has been that of "decision support." Today, this area is more important than ever. Working in dynamic and ever-changing environments, modern-day managers are responsible for an assortment of far reaching decisions: *Should the company increase or decrease its workforce? Enter new markets? Develop new products? Invest in research and development?* The list goes on. But despite the inherent complexity of these issues and the ever-increasing load of information that business managers must deal with, all these decisions boil down to two fundamental questions:

- What is likely to happen in the future?
- What is the best decision right now?

Whether we realize it or not, these two questions pervade our everyday lives — both on a personal and professional level. When driving to work, for instance, we have to make a traffic prediction before we can choose the quickest driving route. At work, we need to predict the demand for our product before we can decide how much to produce. And before investing in a foreign market, we need to predict future exchange rates and economic variables. It seems that regardless of the decision being made or its complexity, we first need to make a prediction of what is likely to happen in the future, and then make the best decision based on that prediction. This fundamental process underpins the basic premise of *Adaptive Business Intelligence*.

BACKGROUND

Simply put, Adaptive Business Intelligence is the discipline of combining prediction, optimization, and adaptability into a system capable of answering these two fundamental questions: *What is likely to happen in the future?* and *What is the best decision right now?* (Michalewicz et al. 2007). To build such a system, we first need to understand the methods and techniques that enable prediction, optimization, and adaptability (Dhar and Stein, 1997). At first blush, this subject matter is nothing new, as hundreds of books and articles have already been written on business intelligence (Vitt et al., 2002; Loshin, 2003), data mining and prediction methods (Weiss and Indurkhya, 1998; Witten and Frank, 2005), forecasting methods (Makridakis et al., 1988), optimization techniques (Deb 2001; Coello et al. 2002; Michalewicz and Fogel, 2004), and so forth. However, none of these has explained how to combine these various technologies into a software system that is capable of predicting, optimizing, and adapting. *Adaptive Business Intelligence* addresses this very issue.

Clearly, the future of the business intelligence industry lies in systems that can make decisions, rather than tools that produce detailed reports (Loshin 2003). As most business managers now realize, there is a world of difference between having good knowledge and detailed reports, and making smart decisions. Michael Kahn, a technology reporter for Reuters in San Francisco, makes a valid point in the January 16, 2006 story entitled "Business intelligence software looks to future":

"But analysts say applications that actually answer questions rather than just present mounds of data is the key driver of a market set to grow 10 per cent in 2006 or about twice the rate of the business software industry in general.

'Increasingly you are seeing applications being developed that will result in some sort of action,' said Brendan Barnacle, an analyst at Pacific Crest Equities. 'It is a relatively small part now, but it is clearly where the future is. That is the next stage of business intelligence.'"

MAIN FOCUS OF THE CHAPTER

"The answer to my problem is hidden in my data ... but I cannot dig it up!" This popular statement has been around for years as business managers gathered and stored massive amounts of data in the belief that they contain some valuable insight. But business managers eventually discovered that raw data are rarely of any benefit, and that their real value depends on an organization's ability to analyze them. Hence, the need emerged for software systems capable of retrieving, summarizing, and interpreting data for end-users (Moss and Atre, 2003).

This need fueled the emergence of hundreds of *business intelligence* companies that specialized in providing software systems and services for extracting *knowledge* from raw data. These software systems would analyze a company's operational data and provide knowledge in the form of tables, graphs, pies, charts, and other statistics. For example, a business intelligence report may state that 57% of customers are between the ages of 40 and 50, or that product X sells much better in Florida than in Georgia.[1]

Consequently, the general goal of most business intelligence systems was to: (1) access data from a variety of different sources; (2) transform these data into information, and then into knowledge; and (3) provide an easy-to-use graphical interface to display this knowledge. In other words, a business intelligence system was responsible for collecting and digesting data, and presenting knowledge in a friendly way (thus enhancing the end-user's ability to make good decisions). The diagram in Figure 1 illustrates the processes that underpin a traditional business intelligence system.

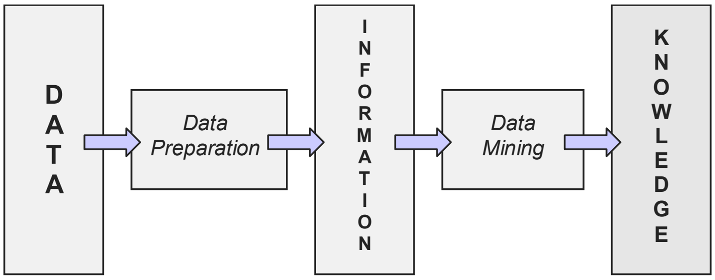
Although different texts have illustrated the relationship between data and knowledge in different ways (e.g., Davenport and Prusak, 2006; Prusak, 1997; Shortliffe and Cimino, 2006), the commonly accepted distinction between data, information, and knowledge is:

- *Data* are collected on a daily basis in the form of bits, numbers, symbols, and "objects."
- *Information* is "organized data," which are pre-processed, cleaned, arranged into structures, and stripped of redundancy.
- *Knowledge* is "integrated information," which includes facts and relationships that have been perceived, discovered, or learned.

Because knowledge is such an essential component of any decision-making process (as the old saying goes, *"Knowledge is power!")*, many businesses have viewed knowledge as the final objective. But it seems that knowledge is no longer enough. A business may "know" a lot about its customers — it may have hundreds of charts and graphs that organize its customers by age, preferences, geographical location, and sales history — but management may still be unsure of what decision to make! And here lies the difference between "decision support" and "decision making": all the knowledge in the world will not guarantee the right or best decision.

Moreover, recent research in psychology indicates that widely held beliefs can actually hamper the decision-making process. For example, common beliefs like "the more knowledge we have, the better our decisions will be," or "we can distinguish between useful and irrelevant knowledge," are not supported by empirical evidence. Having more knowledge merely increases our confidence, but it does not improve the accuracy of our decisions. Similarly, people supplied with "good" and "bad" knowledge often have trouble distinguishing

Figure 1. The processes that underpin a traditional business intelligence system



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