The Evolution of Business Intelligence: From Historical Data Mining to Mobile and Location-based Intelligence

ZELJKO PANIAN
The Graduate School for Economics and Business
University of Zagreb
J.F. Kennedy Sq. 6
CROATIA
zpanian@efzg.hr http://www.efzg.hr/zpanian

Abstract: - Business Intelligence (BI) is today seen as a basis for intelligent business and enterprise systems development and design. But, from the time of its birth in late eighties until nowadays business intelligence has passed a long way. The primary interest of scientists in this field was knowledge discovery. Although the first efforts of scientists were originally oriented towards general knowledge discovery principles and methods soon it became obvious that application of these principles and methods in business environment is perhaps the most promising development perspective. The strong impetus for further research came from Howard Dresner who proposed 'Business Intelligence' (BI) as an umbrella term to describe concepts and methods to improve business decision making by using fact- and knowledge-based support systems. From that time Business Intelligence rapidly evolved through several stages depending on technology used. Improvements in subsequent phases do not derogate those of previous ones but rather complement them, so that BI becomes more and more complex and sophisticated.

Key-Words: - Business intelligence, data mining, OLAP, balanced scorecard, Web mining, Web analytics, dashboards, mobile business intelligence, location-based business intelligence, big data.

1 Introduction

Seeing, understanding and acting in real time is what defines the 'Intelligent Enterprise'. And enterprise agility – the ability to change business and adapt quickly to changing conditions – often may be the difference between organizational success and failure [1].

In the past, enterprise agility has been exceedingly difficult to achieve because viewing all the critical data streaming through the systems, applications, and processes that make up an enterprise's transaction and information data flow, could not be done in cost effective manner [2].

But, things are changing dramatically. Now business information that can be understood in its business context is flowing between applications – and even between our organizations and those of our business partners, customers, and suppliers.

In these circumstances, Business Intelligence (BI) is playing a critical role and must also be available in real time [3].

Business Intelligence rapidly evolved through several stages depending on technology used. Improvements in subsequent phases do not derogate those of previous ones but rather complement them, so that BI becomes more and more complex.

2 The Evolutionary Path of BI

At the very beginning, historical data mining methods and tools were used for strategic managerial reporting purposes.

The second evolutionary stage is characterized by On-Line Analytic Processing (OLAP) technologies and dimensional analysis of data stored in data warehouses and data marts.

In the third stage Balanced Scorecard methodology is used as a means of Business Intelligence creation.

With the emergence and growing popularity of E-Business and other Internet applications and services the new stage of BI appeared since Web analytics and Web mining as a form of BI began to attract the wide professional attention.

The fifth development stage started when usage of Business Dashboard technology became a core component of alerting and alarming systems in business decision-making supported by BI.

Finally, nowadays we are witnessing the era of mobile and location-based Business Intelligence founded on appropriate mobile and location-aware technologies.

As far as it can be seen from today's perspective, the further development in the near future can be expected in the field on unstructured content and so-called big data analysis as a form of sophisticated Business Intelligence.

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3 Stage I: Data Mining

3.1 The Three Parents of Data Mining

Data mining as a methodology has three parents: statistics, computer science, and database/data warehouse management. In the early 1980s, statistics contributed methods such as recursive partitioning and non-parametric regression, and tools such as the bootstrap and cross-validation.

At approximately the same time, computer science developed neural network models and new algorithms for rapid execution of traditional statistical analyses on large data sets, such as clustering and smoothing; they also coined the phrase ‘data mining’.

And database management researchers developed sequential query procedures and relational data bases, as well as the concept of data warehouse. The confluence of these ideas led to the expansion of inferential science to larger and more complex data sets.

3.2 Business Data Mining

Data mining has been very effective in focused areas, such as medical diagnosis, scientific research, and behavioral profiling since the mid-1980s. But, data mining technology has also journeyed into the business world where it has added the new dimension of predictive analysis.

Data mining is a powerful technology that converts detail data into intelligence that businesses can use to predict future trends and behaviors [4]. Some vendors define data mining as a tool or as the application of an algorithm to data.

The truth is data mining is not just a tool or algorithm. Data mining is a process of discovering and interpreting previously unknown patterns in data to solve business problems. Data mining is an iterative process, which means that each cycle further refines the result set. This can be a complex process, but there are tools and approaches available today to help business user navigate successfully through the steps of data mining projects.

From an IT perspective, the data mining process requires support for the following activities:

- Exploring the data
- Creating the analytic set data
- Building and testing the model
- Integrating the results obtained into business applications.

Therefore, the IT organization must provide an environment capable of addressing the following challenges:

- Exploring and pre-processing large data volumes
- Providing sufficient processing power to efficiently analyze many variables (columns) and records (rows) in a timely manner
- Integrating data mining results into the business process
- Creating an extensible and manageable data mining environment

For years, businesses have relied on reports and ad hoc query tools to glean useful information from data. However, as data volumes continue to increase, finding valuable information becomes a daunting task. Data mining technology was designed to sift through detailed historical data to identify hidden patterns that are not obvious to humans or query tools. Many of these previously hidden patterns reveal intelligence that can be integrated into business processes to provide predictive capabilities for improving strategic business decision making.

To be effective in the business world, the data mining process had to be adapted to deliver models in a time-sensitive manner. Today, with the advent of in-database data mining techniques, businesses have finally found it possible and affordable to benefit from the advanced capabilities of this powerful technology.

Data mining makes analytical business applications smarter by providing insights into many new areas of the business that would otherwise go unnoticed. By making business applications smarter, data mining translates into a higher return on business investment.

3.3 The Way Data Mining Is Deployed

An organization cannot simply buy a data mining product, apply it to data and expect to generate a meaningful model [5]. Data mining models are built as part of a data mining process – an ongoing process requiring maintenance throughout the life of the model.

The data mining process is not linear, but an iterative process where you loop back to the previous phase. For example, the initial model you create may lead to insight requiring you to return back to the data pre-processing phase to create new analytical variables. The data mining process contains four high-level steps [6]:

- Define the business problem
- Explore and pre-process the data
- Develop the data model, and
- Deploy knowledge.

Although each of these steps is important, most of time will be spent in the data exploration and pre-processing phase. A well structured data warehouse can significantly reduce the pain felt in this phase.

4 Stage II: On-Line Analytical Processing (OLAP)

4.1 OLAP Basics

OLAP means many different things to different people, but the definitions usually involve the terms ‘cubes’, ‘multidimensional’, ‘slicing & dicing’ and ‘speedy-response’ [7]. OLAP is all of these things and more, but it is also a misused and misunderstood term, in part because it covers such a broad range of subjects.

OLAP is an acronym, standing for ‘On-Line Analytical Processing’. This, in itself, does not provide a very accurate description of OLAP, but it does distinguish it from OLTP or ‘On-Line Transactional Processing’.

It is easy to question the need for OLAP. If an end user requires high-level information about their company, then that information can always be derived from the underlying transactional data, hence we can achieve every requirement with an OLTP application. Were this true, OLAP would not have become the important topic that it is today. OLAP exists and continues to expand in usage because there are limitations with the OLTP approach. The limits of OLTP applications are seen in three areas.

OLAP applications differ from OLTP applications in the way that they store data, the way that they analyze data and the way that they present data to the end-user. It is these fundamental differences that allow OLAP applications to answer more sophisticated business questions.

OLAP applications present the end user with information rather than just data. They make it easy for users to identify patterns or trends in the data very quickly, without the need for them to search through mountains of ‘raw’ data. Typically this analysis is driven by the need to answer business questions such as ‘How are our sales doing this month in South-Eastern Europe?’ or ‘From which supplier, X, Y or Z, we have ordered the largest quantities of goods needed?’[8].

From these foundations, OLAP applications move into areas such as forecasting and data mining, allowing users to answer questions such as ‘What are our predicted labor costs for next year?’ and ‘Show me our most successful salesman’.

4.2 Multidimensionality

Although different OLAP tools use different underlying technologies, they all attempt to present data using the same high-level concept of the multidimensional cube. Cubes are easy to understand, but there are fundamental differences between cubes and databases that can make them appear more complicated than they really are.

The cube is the conceptual design for the data store at the center of all OLAP applications. Although the underlying data might be stored using a number of different methods, the cube is the logical design by which the data is referenced.

The axes of the cube contain the identifiers from the field columns in the database table. Each axis in a cube is referred to as a ‘dimension’. The basic logical construct is a simple two-dimensional cube. Although useful, this cube is only slightly more sophisticated than a standard database table. The capabilities of a cube become more apparent when we extend the design into more dimensions. Multidimensionality is perhaps the most ‘feared’ element of cube design as it is sometimes difficult to envisage.

Although the word ‘cube’ refers to a three-dimensional object, there is no reason why an OLAP cube should be restricted to three dimensions. Many OLAP applications use cube designs containing up to ten dimensions, but attempting to visualize a multidimensional cube can be very difficult. The first step is to understand why creating a cube with more than three dimensions is possible and what advantage it brings.

4.3 The Key Differences between OLAP and Data Mining

OLAP is a Business Intelligence tool that allows a business person to analyze and understand particular business drivers in ‘factual terms’. Typically, a specific ‘descriptive’ or factual question is formulated and either validated or refuted through ad hoc queries. OLAP results are also factual results.

Data mining, on the other hand, is a form of discovery-driven analysis where statistical and machine-learning techniques are used to make predictions or estimates about outcomes or traits before knowing their true values. With data mining, predictions are accompanied by specific estimates of the sources and number of errors that are likely to be made. Estimates of errors translate directly to estimates of risk.

Consequently, with data mining, making business decisions in the presence of uncertainty can be done with detailed and reliable information about associated risks. Data mining techniques are used to find meaningful, often complex, and previously unknown or hidden patterns in data.

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5 Stage III: Balanced Scorecards

Robert S. Kaplan and David Norton, co-creators of the Balanced Scorecard Method, wrote their first book in 1996 [9].They looked at the Balanced Scorecard as a Performance Management system that could be used in any size organization to align vision and mission with customer requirements and day-to-day work, manage and evaluate business strategy, monitor operation efficiency improvements, build organizational capacity, and communicate progress to all employees. The scorecard allows an organization to measure financial and customer results, operations, and organizational capacity.

The Balanced Scorecard (BSC) has migrated over time to become a full Performance Management system applicable to both private sector and public (and not-for-profit) organizations. And the emphasis has shifted from just the measurement of financial and non-financial performance, to the management (and execution) of business strategy. In this sense, BSC became a new style of Business Intelligence.

BSC systems can be the heart of a corporate performance system. They provide the ability to view three different dimensions of an organization's performance: Results (financial and customer), Operations, and Capacity.

The components of a fully developed scorecard system are:

- *Business Foundations*, including vision, mission, and values;
- *Plans*, including communications, implementation, automation, and evaluation plans, to build employee buy-in and communicate results;
- *Business Strategies and Strategic Maps*, to chart the course and define the logical decomposition of strategies into activities that people work on each day;
- *Performance Measures*, to track actual performance against expectations;
- *New Initiatives*, to test strategic assumptions;
- *Budgets*, including the resources needed for new initiatives and current operations;
- *Business and Support Unit Scorecards*, to translate the corporate vision into actionable activities for departments and offices; and
- L*eadership and Individual Development*, to ensure that employee knowledge, skills and abilities are enhanced to meet future job requirements and competition.

In BSC language, vision, mission, and strategy at the corporate level are decomposed into different views, or perspectives, as seen through the eyes of business owners, customers and other stakeholders, managers and process owners, and employees. The owners of the business are represented by the Financial perspective; customers and stakeholders (customers are a subset of the larger universe of stakeholders) are represented by the Customer perspective; managers and process owners by the Internal Business Processes perspective; and employees and infrastructure (Capacity) by the Learning and Growth perspective.

But, building and implementing a scorecard system is one thing; turning the scorecard into a used and useful BI system is something else entirely.

The key to transforming a scorecard into a BI system is to start at the right level of granularity and 'connect the dots' among the components of strategy (mission, vision, values, pains, enablers, strategic results and themes, and strategic objectives) and the components of operations (projects, processes, activities, and tasks), and the budget formulation and cost reporting processes [10]. Performance measures tie the parts together, and give an organization a way to measure how successful they are at achieving their goals.

6 Stage IV: Web Mining and Web Analytics

With the explosive growth of information sources available on the World Wide Web, as well as various E-Business activities, it has become increasingly necessary for users to utilize automated tools in finding the desired information resources, and to track and analyze their usage patterns. These factors give rise to the necessity of creating server-side and client-side intelligent systems that can effectively mine for knowledge. That is the reason why a plenty of Web Mining and Web Analytics tools are developed.

6.1 Web Mining

Web mining can be broadly defined as the discovery and analysis of useful information from the World Wide Web [11]. This describes the automatic search of information resources available on-line, i.e. Web content mining, and the discovery of user access patterns from Web servers, i.e., Web usage mining.

6.1.1 Web Content Mining

The lack of structure that permeates the information sources on the World Wide Web makes automated discovery of Web-based information difficult. Traditional search engines such as Lycos, Alta Vista, WebCrawler, and others provide some comfort to users, but do not generally provide structural information nor categorize, filter, or interpret documents.

In recent years these factors have prompted researchers to develop more intelligent tools for information retrieval, such as intelligent Web agents, and to extend data mining techniques to provide a higher level of organization for semi-structured data available on the Web. We summarize some of these efforts below:

1. *Agent-based Approach* – Generally, agent-based Web mining systems can be placed into the following three categories:
   a. intelligent search agents
   b. information filtering/categorization
   c. personalized Web agents
2. *Database Approach* – Focused on techniques for organizing the semi-structured data on the Web into more structured collections of resources, and using standard database querying mechanisms and data mining techniques to analyze it:
   a. multilevel databases
   b. Web query systems

6.1.2 Web Usage Mining

Web usage mining is the automatic discovery of user access patterns from Web servers. Organizations collect large volumes of data in their daily operations, generated automatically by Web servers and collected in server access logs. Other sources of user information include referrer logs which contain information about the referring pages for each page reference, and user registration or survey data gathered via CGI scripts.

Most existing Web analysis tools provide mechanisms for reporting user activity in the servers and various forms of data filtering. But, in recent times more sophisticated systems and techniques for discovery and analysis of patterns are also emerging. These tools can be placed into two main categories, as listed below:

1. *Pattern Discovery Tools* – The emerging tools for user pattern discovery use sophisticated techniques from AI, data mining, psychology, and information theory, to mine for knowledge from collected data.
2. *Pattern Analysis Tools* – Once access patterns have been discovered, analysts need the appropriate tools and techniques to understand, visualize, and interpret these patterns.

One of the open issues in data mining, in general, and Web mining, in particular, is the creation of intelligent tools that can assist in the interpretation of mined knowledge. Clearly, these tools need to have specific knowledge about the particular problem domain to do any more than filtering based on statistical attributes of the discovered rules or patterns.

In Web mining, for example, intelligent agents could be developed that based on discovered access patterns, the topology of the Web locality, and certain heuristics derived from user behavior models, could give recommendations about changing the physical link structure of a particular site.

6.2 Web Analytics

Not very long ago, who was visiting Web sites and why was essentially a mystery. Web masters put counters on Web pages to track how many times people ‘hit’ the page –that is, visited, downloaded a file, or some other activity – but that was the extent of the insight. True Web analytics capabilities were limited to large corporations that could afford to spend thousands of dollars per month on software to track and report on web activity [12].

Today, there is a wide range of Web metrics measuring and tracking applications available, making analytics one of the most talked about topics both online and off. Although some of these tools are still expensive, a number of analytics programs available now are completely free – and just as effective.

Simply put, Web analytics involves measuring, collecting, analyzing, and reporting Web site traffic and behavior with the end goal of optimizing the success of the Web site.

All Web analytics tools work by collecting raw data about Web site visitors and organizing it in a way that is easier to view and understand. Some programs, called log analyzers, use server logs (data files collected by web servers) to provide information about visitors. Then there are other programs – analytics applications – which use bits of code installed on a Web site to gather information about web activity and generate reports.

Generally, log analyzers are considered more technical and the raw information they provide may be hard to understand, especially for people who are unfamiliar with Web metrics. In this case, it is probably a better idea to stick with an analytics program.

No matter which Web analytics tool is used, their users are going to be presented with a robust array of metrics. From page views and unique visitors, to referrers and average time on site, there are endless amounts of data to sift through. But, focusing on the following key metrics will tell users almost everything they need to know [13]:

- *Visitors* – The number of visitors to Web site will give a general idea of how well the Web site owner is getting the word out about his business.
- *Page Views* – Looking at page views can tell what content on the site is the most popular.
- *Referring Sites* – Looking at referring sites will give an excellent snapshot of the type of people who are visiting the particular site.

- *Bounce rate and Exit pages* – A bounce rate measures something different than an exit page, but both can give important insights into why people are leaving the site. In most analytics programs, a "bounce" is recorded when a person visits and leaves within a second or two, usually before the page is even done loading. Top exit pages show which pages people visit immediately before they leave.
- *Keywords and Phrases* – Keywords and phrases let the Web site owner know what terms people are using to find his site in search engines. This can give him/her some idea of how to add different content to appeal to even more customers.

Though still a relatively new invention, Web analytics is becoming an increasingly popular – and effective – Web site optimization tactic used by online business owners. By providing deep insight into the who, what, when, why and how of web site traffic and visitor behavior, Web analytics tools can help you improve the usability of the site and boost its effectiveness.

7 Stage V: Business Dashboards

Business Dashboards are becoming the new face of business intelligence (BI) at the very beginning of the 21st century. While on the surface, Executive Information Systems (EIS) from the 1980s had a similar look and served a similar purpose, modern Dashboards are interactive, easier to set up and update to changing business needs, and much more flexible to use. This, plus their ability to present data and information at both a summary and detailed level, makes them one of the most powerful tools in the business user's kit.

To be useful, however, a Business Dashboard must be implemented around the needs of the business [14]. Its functions should not be dictated by technology or by the whims of the end users. Also, a Business Dashboard should be implemented so that it gets used – and so that the decision-makers employing it can act on the information the Dashboard presents.

7.1 Business Dashboards vs. Spreadsheets

Along with modern Dashboards evolving from the old EIS tools, another BI tool has been with us for a while: the spreadsheet. Most often in the form of Microsoft Excel, the spreadsheet has an intuitive interface and is easy to learn, at least as far as its most basic functions. It provides detailed numbers, which users can analyze adding their own calculations.

However, while the spreadsheet is easy to use and understand, it is often too detailed to give a quick and comprehensive overview of business data. Furthermore, users are likely to reformat this business data in other spreadsheets, adding calculations and aggregations. This will create yet more cells of important business data. Although it is possible to create complementary charts in most spreadsheets, this is a time consuming, manual activity that lends itself to easily-made mistakes.

Nonetheless, many business users stick with spreadsheets because they feel comfortable with them and are reluctant to change to another model. The reality is that not everything can be done efficiently in the spreadsheet; and one should not get stuck with them simply because that is what they have or have been using. This can lead to a situation where it's the limitations of the program – rather than business needs – that determine the scope of reporting and analysis.

With the right underlying technology, today's Business Dashboards stand out from the spreadsheet, which nevertheless remains the most used BI interface today. Dashboards allow for a quick and easy-to-personalize overview of critical business data in a timely fashion. This added value turns today's Business Dashboards into the new face of BI.

7.2 Business Dashboards vs. Scorecards

In many cases, the terms Dashboard and Scorecard are used almost interchangeably. But, although Dashboards and Scorecards have much in common, there are the differences between the two [15]. On the one hand, executives, managers, and staff use Scorecards, and particularly Balanced Scorecards, to monitor strategic alignment and success with strategic objectives and targets.

On the other hand, Business Dashboards are used at operational and tactical levels. Managers, supervisors, and operators use operational Dashboards to monitor detailed operational performance on a weekly, daily, or even hourly basis. In the same vein, managers and staff use tactical Dashboards to monitor tactical initiatives.

7.3 Benefits of Business Dashboards Deployment

Business Dashboards help organizations reach stated goals by leveraging information and analytics. They provide alignment, visibility, and collaboration across the organization by allowing business users to define, monitor, and analyze business performance via key performance indicators (KPIs). Whether organizations choose to implement strategic or tactical performance management initiatives, dashboards can provide the

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foundation for enabling organizations to more effectively align their business strategy with execution.

In defining, tracking, and analyzing performance indicators, Business Dashboards can provide users with the following capabilities:

- *Root-cause analysis* – They provide the ability to drill down on a Key Performance Indicators (KPIs) to a more detailed report revealing the underlying business activity driving the higher-level indicator output. This permits analysis of causative factors and enables corrective action.
- *Time-series analysis* – Dashboards provide the ability to track and analyze key metrics over time and to identify trends and exceptions.
- *Rules, alerts and alarms* – They provide the ability to track and monitor a plenty of business processes and receive real-time notifications when they are out of alignment. Once a notification has been received, business users can examine the irregularity, perform proactive root-cause analysis, and take corrective action.
- *Predictive analysis* – Dashboards provide the ability to forecast, model, and analyze complex relationships. Predictive analysis is necessary to better understand the future impact of decisions and the key influencers of future business behaviors (e.g., churn and repeat purchase).
- *Segment analysis* – Business Dashboards provide the ability to define, manage, and understand the behavior of business groupings such as strategic customer segments, departments, and regions. Segmentation can be used in defining metrics and in providing root-cause analysis.
- *Statistical process control* – They provide the ability to monitor and track variables via control charts and statistical analysis, commonly used in quality control programs such as Six Sigma and Total Quality Management.

Many organizations also want to deploy the Business Dashboard in more sophisticated and intricate application contexts such as with an analytic application deployment or as an extranet that reaches beyond the corporate boundaries. According to Carotenuto [16], synergies between Business Dashboards and other BI applications lead to improvements in both.

8 Stage VI: Mobile and Location-based Intelligence

8.1 Mobile Intelligence

Computing is entering its new era with desktop Internet applications giving way to a new generation of Mobile Internet applications. The use of the Internet on smartphones and other mobile devices has changed the way people communicate and consume information, creating an exponential rise in the acceptance, adoption, and usage of data [17]. With the ability to access information at any time, in any location, on a hand-held device, consumers can now make more and more decisions quickly and easily.

As consumers capitalize on the power of mobile devices, the same transformation is occurring in business. Business applications that were mildly successful when used on a desktop, have become highly effective and valuable when consumed on the go, whenever and wherever business is conducted.

The revolutionary impact of Mobile Intelligence is evidenced by three major drivers [18]:

1. *Mobile Intelligence expands the user population by a factor of 10* – Mobile devices will significantly surpass the impact and number of desktop Internet devices. The range and number of mobile devices is showing explosive growth and the boundaries between these devices is blurring. Mobile computing devices now range from smartphones and tablets to handheld game consoles and fully functional in-car computers. For all their differences, these mobile device types harmonize across themes of connectivity, mobility, and information delivery.
2. *Mobile intelligence expands information opportunities by at least a factor of 10* – As mobile computing becomes pervasive in both personal and professional lives, people are discovering more and more opportunities to make complete use of these powerful devices. From the moment they wake, they can use applications that not only enhance their personal lives but also make them more productive and effective at work. The ability to access information at anytime in any location, easily in the palm of a hand, allows immediate decision-making.
3. *Mobile intelligence expands personal query relevance by a factor of 4* – Today's mobile computing devices are revolutionizing how information is deposited into applications. Using a keyboard and a mouse is now outdated. A natural user interface allows users to point at what they want, touch where they want to go, and move the device to indicate how they want to explore the information. Mobile computing devices respond to how users move their fingers and arms, and understand their location, the direction they are moving, and how fast. Mobile devices use these natural actions as inputs. Touch screens dynamically change into

convenient input controls to meet the user's needs, such as a keyboard, a calculator, a map, and a data visualization control. As a result, the user's inputs are faster and cover a greater range of options, all while being more intuitive.

The ongoing impact of the evolution in device inputs and natural interfaces is to make BI applications faster, easier, and more natural to use, leading to greater usage and a higher user adoption rate.

8.2 Location-based Intelligence

Almost all organizations give at least passing attention to the characteristics of location, whether in evaluating traffic patterns in choosing a factory location, determining optimal travel routes, or calculating market wages in deciding where to site an industrial plant. There is certainly benefit even in these isolated, often unstructured observations. But assessing the impact of location in this way – call it 'location inference' [19] – is a little like stargazing without a telescope.

Although less familiar than giant telescopes, the software and analytical tools necessary for systematically probing location-based data closer to home are just as well developed, and offer willing companies a far richer and more informed perspective on their physical operating environment than is possible with more casual analyses.

These tools allow companies not only to observe and collect data describing even the hidden, business-relevant features of their location, but also to probe and deploy this data in a way that greatly enhances understanding of the impact of location and, ultimately, enables organizations to dramatically reduce costs, increase revenues, and boost profits. Such tools thus help to translate the notational "location inference" into a much more powerful form of location-based knowledge called *Location-based Intelligence (LBI)*.

Conceptually, LBI bears many similarities to the *customer intelligence* concept that grew to prominence during the 1990s and that underlies such well-known technology solutions as *customer relationship management* software, more commonly known as CRM. The core premise of customer intelligence and CRM software in particular was that, if a company knew more about a particular customer's demographics, preferences, and buying habits over time, it could tailor marketing offers and customer interactions in a way that would increase the customer's propensity to buy and, in general, boost the customer's overall lifetime value.

As noted, LBI has also been part of business operations for decades, at least in a rudimentary form. For instance, long before the advent of computers, delivery firms planned pick-ups and drop-offs so as to minimize travel time and fuel use. Retailers and service franchise owners like supermarkets and car repair shops typically have taken a number of factors into account before deciding where to locate their businesses. And, of course, real estate agents have long known that home values are determined primarily by three factors: 'location, location, and location'.

As obvious as these examples are, they represent only a fraction of the actionable intelligence inherent in a company's location, and a small portion of the value that can be obtained today from sophisticated LBI tools. Location and its business-relevant implications, in fact, infuse nearly all business operations: every organization with a physical presence exists somewhere, and the same is true of nearly all of that organization's customers and suppliers.

These and many comparable examples confirm that LBI is just what it appears to be: invaluable organizational intelligence, drawn from both the organization's and customers' locations that can enhance the understanding of the organization's operating environment, and so be used to increase revenues, reduce costs, and improve profits. It is the same kind of value that CRM-style analytical solutions began bringing to customer-facing organizations a decade before.

And like those customer intelligence solutions, which depended heavily on advanced information technologies for their analytical and data-management power, so too are LBI solutions now being powered, not by gut instinct and consensus "guessing," but by advanced analytical and data-processing tools that can detect patterns, risks, and opportunities that otherwise would be invisible to human 'eyeball' analysis.

9 The Future: Business Intelligence from Big Data

For decades, companies have been making business decisions based on transactional data stored in relational databases. Beyond that critical data, however, is a potential treasure trove of nontraditional, less structured data – Web logs (blogs), social media, e-mail, sensors, and photographs – that can be mined for useful information.

Decreases in the cost of both storage and computing power have made it feasible to collect this data, which would have been thrown away only a few years ago. As a result, more and more companies are looking to include nontraditional (yet potentially valuable) data with traditional enterprise data in their business intelligence analysis.

'Big data' typically refers to nontraditional data, which can be characterized by four parameters: volume, variety, velocity, and value [20]. Typically, big data is

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generated in much greater quantities than traditional enterprise data, is produced on a more frequent basis and in a wider range of ever-changing formats, and will vary greatly in its economic value.

When big data is distilled and analyzed in combination with traditional enterprise data, companies can develop a more thorough and insightful understanding of their business, which can lead to enhanced productivity, a stronger competitive position, and greater innovation – all of which can have a significant impact on a company's bottom line.

Big data by itself, regardless of the type, is worthless unless business users do something with it that delivers value to their organizations. That is where Business Intelligence comes in. Although organizations have always run reports against data warehouses, most have not opened these repositories to ad hoc exploration.

A valuable characteristic of big data is that it contains more patterns and interesting anomalies than 'small' data [21]. Thus, organizations can gain greater value by mining large data volumes than small ones. While users can detect the patterns in small data sets using simple statistical methods, ad hoc query and analysis tools or by eyeballing the data, they need sophisticated techniques to mine big data.

Big data BI does not change data warehousing or traditional BI architectures; it simply supplements them with new technologies and access methods better tailored to meeting the information requirements of business analysts and data scientists.

The biggest change in the new BI architecture is that the data warehouse is no longer the centerpiece. It now shares the spotlight with systems that manage structured and unstructured data. The most popular among these is Hadoop, an open source software framework for building data-intensive applications.

Hadoop runs on the Hadoop Distributed File System (HDFS), a distributed file system that scales out on commodity servers. Since Hadoop is file-based, developers don't need to create a data model to store or process data, which makes Hadoop ideal for managing semi-structured Web data, which comes in many shapes and sizes. But because it is 'schema-less', Hadoop can be used to store and process any kind of data, including structured transactional data and unstructured audio and video data [22].

However, the biggest advantage of Hadoop right now is that it is open source, which means that the up-front costs of implementing a system to process large volumes of data are lower than for commercial systems. However, Hadoop does require companies to purchase and manage tens, if not hundreds, of servers and train developers and administrators to use this new technology.

The BI architecture of the future will incorporate traditional data warehousing technologies to handle detailed transactional data and file-based and non-relational systems to handle unstructured and semi-structured data. The key is to integrate these systems into a unified architecture that enables casual and power users to query, report and analyze any type of data in a relatively seamless manner.

This unified information access is the hallmark of the next generation BI architecture.

10 Conclusion

The world of business is constantly changing and Business Intelligence solutions are trying to keep pace [23]. In 1980s, when first BI solutions appeared, the focus was on mining historical data in attempts to recognize important patterns which could make business more important. From that time BI has passed a long way.

From today's point of view we can indentify at least six evolutionary stages in the field of Business Intelligence: the first one in which data mining emerged, the second one which is characterized by OLAP techniques invention and implementation, the third one when Balanced Scorecards methodology was developed, the fourth stage in which proliferation of E-Business activities made it possible to implement efficient Web mining and Web analytics methods, the fifth one in which Business Dashboards shaped the face of BI, and, finally, the sixth stage when mobile technologies promoted Mobile and Location-based Intelligence.

And today, we are entering the further development stage in which the major source of Business Intelligence will be unstructured information content and so-called big data.

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