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BIG DATA AND BUSINESS SUPPORT: STRATEGIES AND CHALLENGES

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Abstract

In recent years, the world has witnessed a growth in electronic data resulting from advancement in computing technologies. Making sense out of this data has evolved from decision support, to executive support, to online analytical processing, to business intelligence, to analytics and now to big data. As a result, researchers are getting interested to study approaches, uses and challenges associated with this emergence of big data. This survey reviews the literature, on big data in aspects of strategic use, predictive analytics, visual challenges, security challenges and paralysis by analysis. The paper concludes that there is lots of data to analyse and it is perfect to get as much information, knowledge and understanding from the data but it is vital that one seriously reviews the supposed reality against the model and the model against the supposed reality.

Keywords: Business Analytics, Big data, Predictive analytics, Visual Analytics, Visualisation

INTRODUCTION

We are living in the knowledge age where information and knowledge has become one of the most sought after commodity as characterized by proliferation of digital devices and computing systems. And as such, Data is being generated and collected in unprecedented volumes, giving rise to the concept of "Big Data". According to Victoria et. al. (2014), Big Data comprises data at the scale of exabytes, zettabytes or yottabytes. It is data "with sizes beyond the ability of commonly used software tools to capture, curate, manage, and process the data within a tolerable elapsed time". Victoria et. al notes that Big Data is not just the increasing volume or amount of data, but also its velocity (speed of data in and out), variety (range of data types and sources) and veracity (the biases, noise and abnormality in data).

Over the last 45 years, the general activity of making sense of data has evolved from decision support, to executive support, to online analytical processing, to business intelligence, to analytics and now to "big data" (Davenport, 2014). Bigdata can be defined as the collection and interpretation of massive data sets, made possible by vast computing power that monitors a variety of digital streams such as sensors, market place interactions and social information exchanges, and analyses them using "smart" algorithms. The main objectives of big data are: (1) bring about dramatic cost reductions, (2) substantial improvements in the time required to perform a computing task, or new product and service offerings and (3) support internal business decisions. As the complexity and dynamics of the business context and markets increase, the need for accurate, pertinent and immediate information will continue to grow (Shuliang Li, 2004). Today it costs little to collect data since it is a by-product of information technology developments that are an integral part of modern organizations. There is therefore increased data from many sources, including retail point-of-sale purchases, online transactions, medical, educational and governmental records, global positioning systems, RFID (radio frequency identification devices), wireless electronic data sensors, and so on.

There is a clear and present need to exploit the available data and technologies to develop the next generation of business applications that can combine data-dictated methods with domain specific knowledge. Analytical information technologies are particularly suited for these tasks. These technologies can facilitate both automated and human expert driven knowledge discovery and predictive analysis, and can also be made to utilize the results of models and simulations that are based on business insights.

STRATEGIC USE OF BIG DATA TO SUPPORT INTERNAL BUSINESS DECISIONS, DISCOVERY AND PRODUCTION

Big data may be new for startups and for online firms, but many large firms view it as something they have been wrestling with for a while. According to Davenport (2013), there are three aspects of big data that impresses managers in large firms: the lack of structure, the opportunities presented, and low cost of the technologies involved.

Big data burst upon the scene in the first decade of the 21st century, and the first organizations to embrace it were online and startup firms like Google, eBay, LinkedIn, and Facebook (Davenport, 2013). These firms didn't have to reconcile or integrate big data with more traditional sources of data and the analytics performed upon them, because they didn't have those traditional forms. Making sense out of big organisational data has evolved prompting a change in terminology as shown on the table below:

Table 1: Evolution of terminology for using and Analyzing data

Term	***Time frame***	***Specific meaning***
Decision support	1970–1985	Use of data analysis to support decision making
Executive support	1980–1990	Focus on data analysis for decisions by senior executives
Online analytical processing (OLAP)	1990–2000	Software for analyzing multidimensional data tables
Business intelligence	1989–2005	Tools to support data-driven decisions, with emphasis on reporting
Analytics	2005–2010	Focus on statistical and mathematical analysis for decisions
Big data	2010–present	Focus on very large, unstructured, fast-moving data

Adapted from Big Data@Work: Dispelling the Myths, Uncovering the Opportunities by Thomas H. Davenport (Harvard business Review Press, 2013 in Davenport, 2014)

Intense competition is forcing companies to develop innovative marketing activities to capture customer needs and improve customer satisfaction and retention. Businesses can benefit significantly in their strategy from analyzing customer data to determine their preferences and thus improve marketing decision support.

Customer Satisfaction

Nowadays it's possible to use big data analysis methods on new, less-structured data sources and utilize the resulting information to make better internal decisions. The decision is the same as in the past – how to identify a dissatisfied customer – but the tools are different (Thomas 2009).

Customer Journeys

A number of major financial services firms are also using big data to understand aspects of the customer relationship that they couldn't previously get at. They are using "customer journeys" through the tangle of websites, call centers, tellers and other branch personnel to better understand the paths that customers follow through the organization, and how those paths affect attrition or the purchase of particular financial services.

To address climate change from a global leadership level, the United Nations Secretary-General has Global Pulse hosted the Big Data Climate Challenge to unearth data-driven climate solutions, and developed a social media monitoring dashboard on climate change. This tool analyzes millions of tweets in English, Spanish and French to look at both volume and content of online conversations which include climate change related keywords.

Supply Chain Risk

In supply chain decisions, companies are increasingly using external data to measure and monitor supply chain risks. External sources of supplier data can furnish information on suppliers' technical capabilities, financial health, quality management, delivery reliability, weather and political risk, market reputation, and commercial practices. The most advanced firms are monitoring not only their own suppliers but their suppliers' suppliers.

Competitive Intelligence

Competitive and market intelligence used to be a rather intuitive exercise, but big data is beginning to change that approach. If you can get more detailed data and do more systematic analysis on it, the activity will probably improve your strategic decisions.

Pricing

Pricing has a long history of applying analytics successfully. Almost every airline and hotel chain, for example, now uses pricing optimization tools to determine the best price for a seat or room. Pricing optimization was originally done with internal structured data on what goods historically sold at what price, and that's still a key element.

Discovery and Experimentation

Perhaps the highest and best use of big data – mining it for discovery and experimentation – is still in the learning phase in most companies (Thomas 2009). To date, the primary focus of business and technology organizations has been to automate data analysis processes such as marketing, sales and service. Analytics has been used to understand and tune such business processes, keeping management informed and alerting them to anomalies – "exception reporting" has been a key aspect of business intelligence.

Analytics in CRM

CRM is a customer-focused business strategy designed to optimize revenue, profitability, and customer loyalty. By implementing a CRM strategy, an organization can improve the business processes and technology solutions around selling, marketing, and servicing functions across all customer touch-points (B.Santhosh et al 2013).

Due to the aggressive market competition in all sectors, it is critical that organisations should adopt new strategy like CRM technology to assist employees, serve customers better and improve organization performance. Findings by (Abdul et al 2014) suggest that CRM technology is associated with the four dimensions of organization performance (i.e. financial, customer, internal process and learning and growth)

PREDICTIVE ANALYTICS IN MARKETING KNOWLEDGE CREATION

Rapid technological evolution, consumerism and the internationalization of competition are merely some of the market conditions which result in increased levels of competitive intensity. Dealing with such challenges requires that companies become more adaptive to their market environment (Spiros P. et al, 2007).

To benefit from these technological advancements that have made data available at little cost, data mining and predictive analytics are increasingly becoming popular 'because of the substantial contributions they can make in converting information to knowledge' (Joe, 2007). The need therefore for predictive analytics will continue to grow. Predictive analytics and data mining increasingly are being applied in product development, advertising, distribution and retailing, or marketing research and business intelligence.

The heart of predictive analytics is identified by Joe (2007) as statistical techniques developed in the 1920s and the concept of “exploratory data analysis” proposed by the statistician John Tukey of Princeton University in the mid-1970s. In predicting the future, both data mining and predictive analytics perform unique roles though as Joe (2007) notes ‘are sometimes viewed as one and the same’. Data mining first searches for data patterns and identifies promising relationships. Some of the searches used to build the relationships are: data (numbers), text (words or phrases), web movements (click through and time-spent patterns) and visual images. Predictive analytics then uses confirmed relationships to predict future trends, events and behavior patterns.

Predictive analytics mainly thought of as predictive modeling is increasingly including descriptive and decision modeling. It involves extensive data analysis, with each model optimized for different purposes and build on different statistical techniques. Predictive models analyze past performance to assess how likely a customer is to exhibit a specific behavior in the future. The models also seek out elusive data patterns to answer questions about customer performance, such as fraud detection models.

Descriptive models “describe” relationships in data and are used to classify customers, prospects, events or activities into groups. Decision models on the other hand describes the relationship between all the elements of a decision to optimize certain outcomes. This includes what is known about the data and relationships, the decision itself, and the predicted outcome of the decision. Decision models are generally used offline to develop a set of business rules that are likely to produce the desired outcome for customers, events, activities or organizations. Predictive analytics help organizations solve problems or pursue opportunities, and identify relationships as they currently exist or as they are likely to exist in the future through knowledge creation.

MEETING BIG DATA CHALLENGES WITH VISUAL ANALYTICS

Regardless of clear-cut definition, exponential growth, speed and variety in data have created new challenges not only in the management of vast amounts of heterogeneous data, but also in how to make sense of it all. Within organisations, a growing cadre of workers, with titles such as “business analyst”, “data analyst” and “data scientist” are harnessing new tools, practices and solutions (Victoria et. al. 2014). Among these tools is visual analytics (VA), often defined as “the science of analytical reasoning facilitated by interactive visual interfaces” (Victoria et. al. 2014).

As powerful and promising a tool as VA is, difficulties with identifying and "wrangling" the data needed for visual analysis are proving to be major barriers to its adoption and effectiveness.

Information visualisation, VA and the challenge of analysing Big Data

According to Victoria et. al. (2014), as the volume, velocity and variety of data available to business people, scientists and the public increase, effective use of data is becoming more challenging. Standard tools for data analysis and exploration fall short as a means of keeping up to date with the flood of data. The human information processing system simply cannot hold information in working memory long enough to extract relevant patterns from the data. Using visualisation lightens this burden, however, because encoding information visually relieves the demand on our memories and allows patterns to "pop out". An excellent illustration of the use of information visualisation to present patterns and trends in very large data sets is the work of Rosling (2011), whose Gapminder videos eloquently illustrate global population trends over hundreds of years. Rosling's work presents the results of his analysis through information visualisation. Visual analysis, on the other hand, seeks to provide people with tools that create visualisations and, thereby, facilitate analysis, allowing users to understand and examine large data sets through the use of information visualisation. When we interact with an information display, such as a map, diagram, chart, graph or a poster on the wall, we are solving a cognition problem. In the case of a map, it may be how to get from one location to another. In the case of the graph, it may be to determine the trend; for example, is the population increasing or decreasing over time?. What is the shape of the trend?. The answers to our questions can be obtained by a series of searches for particular patterns – visual queries. Visual analysis is a "visual sense-making loop", which moves the analyst from data to knowledge. VA allows the analyst to explore large data sets to "detect the unexpected" (Victoria et. al. 2014). Another way to look at the interplay between information visualisation and VA is that information visualisation is a product, while visual analysis is a process. VA process has been distilled into three distinct phases: (1) data collection and curation; (2) data pre-processing; and (3) analysis – a structure that emerged organically from the research data. The process is said to begin with identification, collection and analysis of the type of data available for display and the type of information the viewer hopes to extract or convey. This is characterised as the "data collection and curation" phase of visual. Next, the analyst needs to define a way to map the data using a VA tool or toolkit. At this stage, the analyst may have to transform the data from one form to another to facilitate the visual analysis. This includes cleaning, integrating, filtering, sampling, sub-setting, aggregating and other forms of data "wrangling" so that the format of the data supports analysis with the specific VA tool(s). This phase also entails data transformation, sometimes also called “shaping” or “modelling” (Ward et al. 2010), which may occur under the user’s control or algorithmically, depending on the amount of machine intelligence built into the VA tool. The final phase is analysis, once the data are pre-processed, mapping of the data to graphic entities within a particular VA tool occurs, e.g. one attribute of the data may be mapped to size, another to colour, another to position etc. It is this visual rendering that the analyst views and interacts with in an iterative, non-linear process of visual querying and sense-making that often involves the use of several data sets and VA .VA is being applied in an increasing number of domains, such as healthcare, finance and culture. Its application to the types of activities that records professionals execute or support within organisations is only just starting to receive exploration. For example, the use of visual analysis for email, development of a VA tool for data de-duplication ,visual analysis to investigate the quality of metadata in a large digital repository (Victoria et. al. 2014).

Fig 1: Big data analysis tool

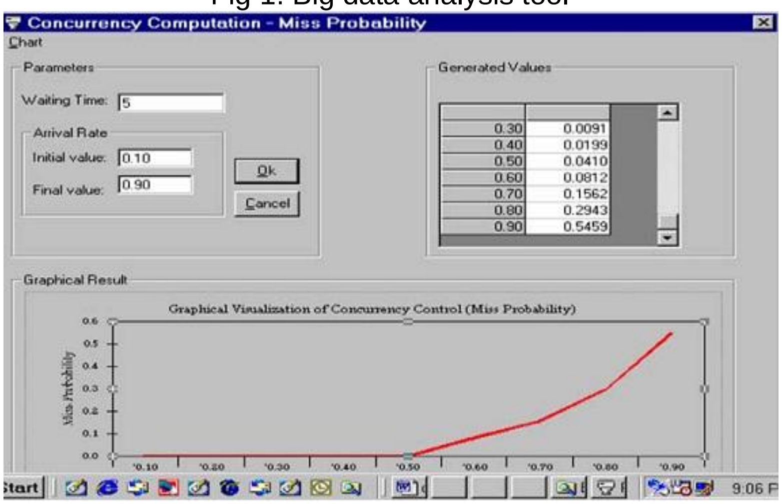
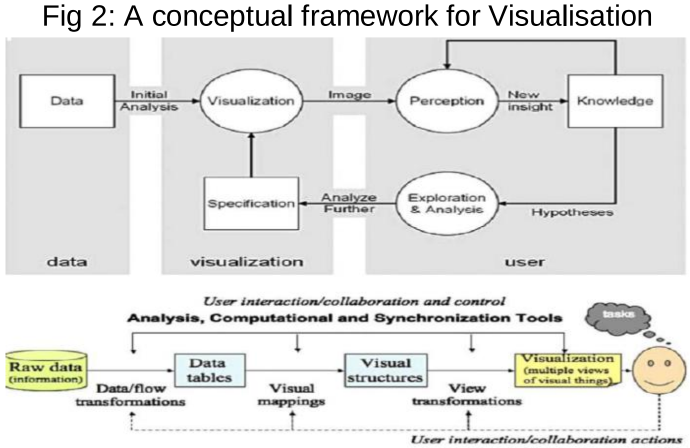


Fig 2: A conceptual framework for Visualisation



Source: Victoria et. al. (2014)

Data Issues as a Barrier to Effective Visual Analysis

As powerful and promising a tool as visual analysis is, difficulties with pre-processing data needed for visual analysis are proving to be major barriers to its adoption and effectiveness. This phase can take up to 80 per cent of the total development cost on an analytics project for example, investigated the day-to-day practices of enterprise analysts from sectors including healthcare, retail, finance and social networking. Data discovery and wrangling, often is the most tedious and time-consuming aspects of an analysis, are not addressed in existing visualisation and analysis tools. Some of challenges to VA include; Unavailability of data, Fragmentation of data, Data quality (missing values eg date field, data format, need for standardisation), Data shaping (for technical compatibility, for better analysis), disconnect between creation/management and use, record keeping (general expression of need for record keeping, Version control) among others. Access to (structured) data sometimes proves to be a barrier to effective visual analysis. Also access may be problematic; identifying that, in some cases, the administrator responsible for granting access to data had already left the company by the time access was requested. With no assigned organisational responsibility for long-term management of the data, the data were essentially lost, Victoria et. al. (2014).

DATA SECURITY CHALLENGES IN BUSINESS ANALYTICS

According to (Sam Curry et al, 2013), Big data's new role in security of information systems comes at a time when organizations confront unprecedented information risk arising from two conditions: 1. Dissolving network boundaries (extranets) **–** the more organizations open as well as extending their data networks by allowing partners, suppliers and customers to access corporate information in new, dynamic ways in order to push collaboration and innovation, the more they become more vulnerable and prone to security of their information based systems. Corporate applications and data are today also increasingly accessed through cloud services and mobile devices, shattering what's left of enterprise network boundaries and introducing new information risks as well as threats. 2. More sophisticated adversaries **–** Cyber attackers have become more adept at waging highly targeted, complex attacks that evade traditional defenses, static threat detection measures and signature-based tools. Often times, cyber-attacks or fraud schemes perpetrated by advanced adversaries aren't detected until well after damage has been done. In today's hyper-extended, cloud-based services, highly mobile business world, pervasive computing, security approaches solely reliant on perimeter defenses or that requires predetermined knowledge of the threat or direct control over all infrastructure elements are being made obsolete. Instead, a more supple approach based on dynamic risk assessments, the analysis of vast volumes of data and real-time security operations is essential to providing meaningful security. As part of modernizing information security programs, organizations will have to reduce their reliance on signature-based scanning tools, which only detect limited-scope threats that have been encountered in the past. The need to cultivate security capabilities that will eventually help them detect the unknown and predict threats in the future.

To move in this direction, (Sam Curry et al, 2013) notes that organizations must gain full visibility into the security conditions of all IT assets handling valuable information. Today, however, most organizations effectively capture and analyze only a relatively small slice of security-related information. Like network logs, system alerts and application access records. Many sources of security-related information have not been used in security operations because their data formats are too variable and unpredictable, the data sets are perceived to be too large and/or the data changes too quickly. Now, with recent advancements in computing power, storage systems, database management and analytics frameworks, no data set is too big or too fast. Despite the challenges of normalizing vast amounts of information from such diverse and dynamic sources, big data plays and will continue an increasingly important role in security. By incorporating big data into security programs, organizations gain richer context for assessing risk and learning what's "normal" for a particular user, group, business process or computing environment.

Leading-edge security operations centers especially those in defense and financial services organizations for example are analyzing massive archives of security data to understand attackers' techniques and to uncover understated indicators that could help identify hidden threats faster, track cyber adversaries and perhaps even predict future attacks. They're applying fraud analysis techniques to reduce unauthorized access to user accounts and corporate resources. It's expected that BA predict big data analytics will have disruptive impact unmanly categories in the information security sector, including network monitoring; user authentication and authorization; identity management; fraud detection; and governance, risk and compliance systems. Eventually, BA is also expected to change the nature of conventional security controls such as anti-malware, data loss prevention and firewalls, essentially the entire security spectrum (Sam Curry et al, 2013).

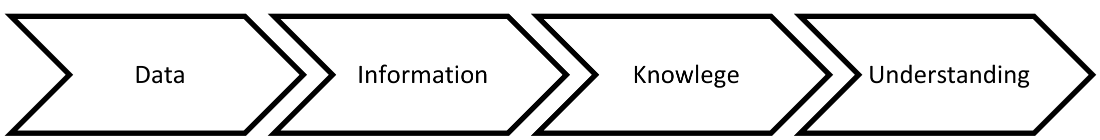
According to (Sam Curry et al, 2013), Integrating business analytics into security operations is and will be the cornerstone of an intelligence-driven security model and will require organizations to rethink how security programs are developed and executed. In updating security programs to take advantage of big data, organizations should consider the following steps: ***1. Set a holistic cyber security strategy*** – Organizations should align their security capabilities behind a holistic cyber security strategy and program that's customized for the organization's specific risks, threats and requirements. The security strategy should integrate business analytics as part of a broader array of technical solutions, combined with tailored processes and expert staff. ***2. Establish shared data architecture for security information* –** Because BA requires information to be collected from various sources in many different formats, a single architecture that allows all information to be captured, indexed, normalized, analyzed and shared is a logical goal. ***3. Migrate from point products to a unified security architecture* –** Developing a unified security analytics framework requires a big-picture, more disciplined approach to security investments than most organizations have shown in the past. Organizations need to think strategically about which security products they will continue to support and use over several years, because each product will introduce its own data structure that must be integrated into a unified analytics framework for security—or deliberately omitted as a potential blind spot. ***4. Look for open and scalable business analytics security tools* –** Organizations should ensure that ongoing investments in security products favor technologies using agile analytics-based approaches, not static tools based on threat signatures or network boundaries. New, big data-ready tools should offer the architectural flexibility to change as the business, IT or threat landscape evolves. **5. Strengthen the security chiefs data science skills** – While emerging security solutions is and will be business analytics ready, security teams may not be. Data analytics is an area where on-staff talent may be lacking. In the past, research indicates lack of a sufficient number of staff with analytics skills, as a key challenge to delivering a successful business intelligence and analytics solution in organizations. ***6. Leverage external threat intelligence* –** Augment internal security analytics programs with external threat intelligence services. Often threat indicators, attack forensics or intelligence feeds from outside sources are not machine-readable and require extensive manual processing by security analysts. Security chiefs should evaluate service providers aggregating threat data from many trustworthy, relevant sources.

BUSINESS ANALYTICS PARALYSIS BY ANALYSIS

Jan (2005) gives the definition of Paralysis by analysis as “a phenomenon occurring when an analysis becomes so large or unclear that one essentially no longer understands what the analysis or its output is about, which results in no action or paralysis”. The opposite of paralysis by analysis is fact based decision making. It is very important to analyse financial business data and even other data affecting the organization so as to gain insights about the competitor, the market and even the organization’s own internal processes. Jan (2005) emphasizes that several studies have shown that there is a high Return on Investment for an organization that is actively using business analytics with some organizations realizing the return on investment even within two years of implementation. That should encourage an organization to use business analytics because of its clear benefits but at the same time be careful on how the organization implements Business analytics for if not done well there is a risk of falling into a case of paralysis by analysis. Sharif (2007) talks about the paralysis by analysis for organizations making decisions on technology, in this fast changing technology world the organizations face a dilemma with too many parameters to evaluate.

Jan (2005) explains that paralysis by analysis is a common problem in the mathematical analysis because the analyst doing the analysis does not understand how to incorporate the understanding of the numbers in to the context of the particular organization. All mathematical analysis use data as input and information is the output of the first level of the business analytics. Information is descriptive and historical and relates to the past and present and is attention directing. Further analysis leads to the information being transformed into knowledge which is predictive or associative and unveils hidden facts. Business analytics does not stop there but for one to fully act upon the knowledge wisely one has to understand the knowledge fully and in the business context that it's being analyzed in. This concept is illustrated in figure 1 below. During Business analytics work it is important to remember the context and the purpose of every analysis because the work has to be looked at with understanding of reality. "BA model is just a model of reality not reality itself so one must seek to understand reality more fully via non-analytical means and bring this understanding to bear on the modeling and its statistics so that both the modeling and the statistics become meaningful" (Jan, 2005) There is a need to have more business users (experts) trained as Business Analysts because they understand the business and thus would have a clearer understanding of the numbers. Data mining makes most sense when there is full understanding of the business.

Fig 3: BA starts with Data which is analyzed and Information is the output, further analysis produces knowledge which when further analyzed becomes understanding.



The probability of paralysis by analysis increases as the number of variables especially output variables in the model increases and does not occur in the case of a single objective business model. Every business analytics model should have clear objectives that have been derived after a very good understanding of the reality behind the numbers. In an article in the Washington Monthly Mooney (2004) describes how the Jim Tozzi a former Regan budget official has used business analytics to end all regulation because every regulation that can be justified with numbers can have the same numbers further analyzed to point out flaws in it. Tozzi has made a career out of looking into studies done by government and other regulatory organizations and pointing out flaws and weaknesses that prevent the organization from using the study to make a regulation. The same data can be analyzed in different contexts to give completely different recommendations.

A fundamental problem that is a root of the paralysis by analysis problem is the indiscriminate use of the central tendency measures like the arithmetic average, weighted average, median and mode which cannot measure dispersion so the use of variance and sample range should be encouraged to curb the problem (Jan 2005). To avoid paralysis by analysis there has to be a systematic way to work a business analytics model by "making the model modular, using precise descriptions in the model and explaining text if necessary, making self-regulating models, using control summations after every step to make sure nothing is lost, and not make large complex equations but break it up into smaller segments" (Jan, 2005). To avoiding falling into the problem two things must happen; first understanding of the result that is the subject matter and second having a clear picture of reality. It is impossible to understand the financial results from a model when one does not understand any finance.

CONCLUSION

In conclusion there is lots of data to analyse and it is perfect to get as much information, knowledge and understanding from the data but it is vital that one seriously reviews the supposed reality against the model and the model against the supposed reality. There is a clear and present need to exploit the available data and technologies to develop the next generation of business applications that can combine data-dictated methods with domain specific knowledge.

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