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Big Data Analytics Services to Boost Intelligence in Business

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Abstract

The usage of big data analytics services to improve business intelligence is examined in this article. More precisely, this paper presents a big data analytics service-oriented architecture (BASOA) and suggests an ontology for big data analytics. It then applies BASOA to business intelligence, and our survey data analysis indicates that the proposed BASOA is feasible for improving enterprise information systems and business intelligence (BI). Additionally, this research investigates relativity, expect ability, and temporality as BI intelligence traits. When it comes to an organization's processes, goods, and services, these are the qualities that decision-makers and customers anticipate from business intelligence. The method suggested in this study may make it easier to conduct research and develop big data science and big data analytics in addition to business analytics and BI.

Keywords*: Big data, big data analytics, e-commerce, business intelligence (BI),intelligent agents, data science.*

I. Introduction

This is the era of big data [1]. Big data and big data analytics have been revolutionizinginnovation, research, development as well as management and business [2, 3, 4]. Big data analytics services have created big market opportunities. For example, the researcher of IDC (International Data Corporation) forecasts that big data and analytics- related services marketing in Asia/Pacific (Excluding Japan) region will grow from US$3.8 billion in 2016 to US$7.0 billion in 2019 at a 16.3% CAGR (compound annualgrowth rate) [5]. Big data and its emerging technologies including big data analytics have been not only revolutionizing the way the business operates but also making traditional data analytics and business analytics bring new big opportunities for academia and enterprises [6, 7, 4, 1]. Big data analytics is an emerging big data technology, and has become a mainstream market adopted broadly across industries, organizations, and geographic regions and among individuals to facilitate big data-driven decision making for businesses and individuals to achieve desired business outcomes [8, 9] [10].

This section proposes an ontology of big data analytics and looks at the interrelationshipbetween big data analytics and data analytics. To begin with, this section first examinesthe fundamental of big data analytics.

Big data analytics can be defined as the process of collecting, organizing and analyzing big data to discover, visualize and display patterns, knowledge, and intelligence as well as other information within the big data [14, 7]. Similarly, big dataanalytics can be defined as techniques used to analyze, acquire and visualize knowledgeand intelligence from big data [14]. Big data analytics is an emerging science and technology involving the multidisciplinary state-of-art information and communication technology (ICT), mathematics, operations research (OR), machine learning (ML), anddecision sciences for big data [6, 2]. The main components of big data analytics includebig data descriptive analytics, big data predictive analytics and big data prescriptive analytics [16, 7]. In other words, big data analytics can be represented as

Big data analytics = big descriptive data analytics + bigpredictive data analytics + big prescriptive data analytics **(1)**

Where + can be explained as “and”. Equation (1) indicates that big data analytics consists of big descriptive data analytics, big predictive data analytics and big prescriptive data analytics, also see Figure 1 below.

Big data descriptive analytics is descriptive analytics for big data [17, 18, 7]，and is used to discover new, nontrivial information [18, p. 2], and explain the characteristics of entities and relationships among entities within the existing big data [19, p. 611]. It addresses the problems such as what happened, and when, as well as what is happening. For example, web analytics for pay-per-click or email marketing data belongs to big data descriptive analytics [20].

Big data predicative analytics is predicative analytics for big data [7, 16], which focuses on forecasting trends by addressing the problems such as what will happen,what's going to happen, what is likely to happen and why it will happen [17, 21, 4].Big data predicative analytics is used to create models to predict future outcomes or events based on the existing big data [19, p. 611]. For example, big data predicativeanalytics can be used to predict where might be the next attack target of terrorists.

Big data prescriptive analytics is prescriptive analytics for big data [7, 16], which addresses the problems such as what we should do, why we should do and what should happen with the best outcome under uncertainty [16, p. 5]. For example, bigdata prescriptive analytics can be used to provide an optimal marketing strategy foran e-commerce company.

From the above analysis, big data descriptive analytics and big data predicative analytics are the solutions to the challenge of big data to the existing descriptive analytics and predicative analytics respectively, in turn, to the existing descriptive datamining and predicative data mining respectively [18, p. 2].

An ontology is a formal naming and definition of a number of concepts and their interrelationships that really or fundamentally exist for a particular domain of discourse[21, 7]. Then, an ontology of big data analytics is an investigation into a number of concepts and their interrelationships that fundamentally exist for big data analytics, asillustrated in Figure 1, based on our early work [7]. In this ontology, big data analyticsis at the top while big data and data analytics are at the bottom. Big data descriptive analytics, big data predictive analytics, and big data prescriptive analytics are below thebig data analytics as its components.

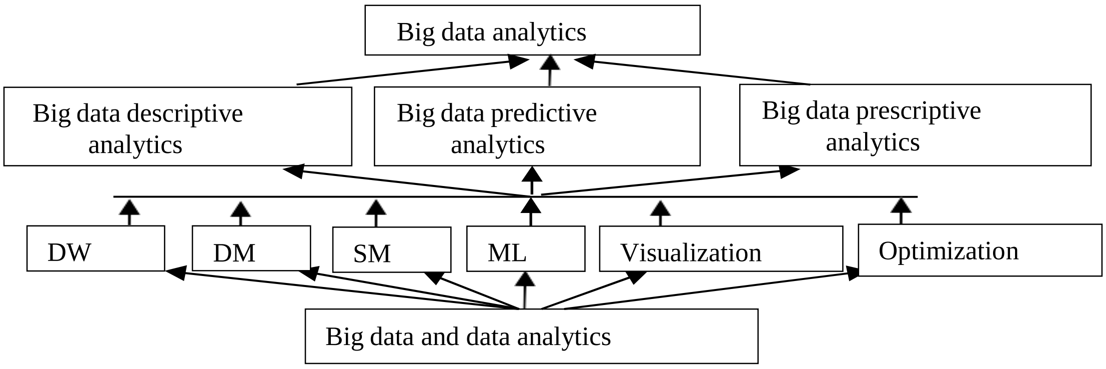

Figure 1. An ontology of big data analytics

In Figure 1, data analytics refers to as a method or technique that uses data, information, and knowledge to learn, describe and predict something [21, p. 341]. In brief, data analytics can then be considered as data-driven discoveries of knowledge, intelligence and communications [17]. More generally, data analytics is a science and technology about examining, summarizing, and drawing conclusions from data to learn, describe, predict and visualize something [6, 7].

The fundamentals of big data analytics consist of mathematics, statistics, engineering, human interface, computer science, and information technology [6, 2]. The techniques for big data analytics encompass a wide range of mathematical, statistical, and modeling techniques [19, p. 590]. Big data analytics always involves historical or current data (often related to operations) and visualization [23]. This requires big data analytics to use DM to discover knowledge from a DW or a big datasetin order to support decision making, in particular in the text of big business and management [21, p. 344]. DM employs advanced statistical tools to analyze the big data available through DWs and other sources to identify possible relationships, patterns and anomalies and discover information or knowledge for business decision making [19, 18]. DW extracts or obtains its data from operational databases as well asfrom external open sources, providing a more comprehensive data pool including historical or current data [19, p. 590]. Big data analytics also uses statistical modeling (SM) to discover knowledge and wisdom through descriptive analysis that can supportdecision making [7]. Visualization technologies including display technologies as an important part of big data analytics make knowledge patterns and information for decision making in a form of figure or table or multimedia. In summary, big data analytics in general and big descriptive data analytics, big predictive data analytics, bigprescriptive data analytics in specific can facilitate business decision making and realization of business objectives through analyzing current problems and future trends,creating predictive models to forecast future opportunities and threats, and analyzing/optimizing business processes based on involved historical or current data toenhance organizational performance using the mentioned techniques [17]. Therefore, big data analytics can be represented below [7].

Big data analytics = Big data + data analytics + DW +DM + SM + ML+(2) Visualization+ optimization

Equation (2) reveals the fundamental relationship between big data, data analytics and big data analytics, that is, big data analytics is based on big data and data analytics,as illustrated in Figure 1. It also shows that computer science and information technology play a dominant role in the development of big data analytics through providing latest techniques and tools of DM, DW, ML and visualization [6, 7]. SM andoptimization still play a fundamental role in the development of big data analytics, in particular in big data prescriptive analytics [16].

It should be noted that Equation (2) is a concise representation for the technologicalcomponents of big data analytics whereas the proposed ontology of big data analytics is to look at what big data analytics constitutes at a relatively high level, also see Equation (1). At a relatively lower level, the ontology also illustrates what technologiesand techniques can support big descriptive data analytics, big predictive data analytics,big prescriptive data analytics, as illustrated in Figure 1.

Apache Hadoop is a platform of big data analytics [1]. As an open source platform for storing and processing large datasets using clusters and commodity hardware, Hadoop can scale up to hundreds and even hundreds of nodes.

Apache Spark is one of the most popular big data analytics services. It has moved from being a component of the Hadoop system, to the big data analytics platform for anumber of enterprises [3, 1]. Spark provides dramatically increased large-scale data processing compared to Hadoop, and a NoSQL database for big data management [19,1]. Apache Spark has provided Goldman Sachs with excellent big data analytics services [3].

We will look at the big data descriptive, predictive and prescriptive analytics as onedimension, and the technological components of big data analytics as another dimension. Then we will provide a 2-dimension analysis for big data analytics as a future research work.

Temporality, Expectability, and Relativity of Intelligence in BI

This section explores the temporality, expectability and relativity of intelligence. It also looks at BI and its relationships with big data analytics.

There are many different definitions on BI from different perspectives. For example,

BI is a framework that allows a business to transform data into information, information into knowledge, and knowledge into wisdom [19, p. 560]. BI has the potential to positively affect a company's culture by creating “business wisdom” and distributing it to all users in an organization. This business wisdom empowers users to make sound business decisions based on the accumulated **knowledge of the business as reflected on recorded historic operational data [19,p. 560].**

BI refers to as a collection of information systems (IS) and technologies that support managerial decision makers of operational control by providing information on internal and external operations [21].

BI is defined as providing decision makers with valuable information and knowledge by leveraging a variety of sources of data as well as structured and unstructured information [24].

The first definition of BI emphasizes that BI is a framework and creates business wisdom for decision makers through business data, information and knowledge and their transformations. The second definition stresses “a collection of IS and technologies” while specifies the decision makers to “managerial decision makers of operational control”, and information to “information on internal and external operations”. The last definition emphasizes BI “providing decision makers with valuable information and knowledge”. Based on the above analysis, BI can be definedas a framework that consists of a set of theories, methodologies, architectures, systems and technologies that support business decision making with valuable data,information, knowledge and wisdom. This definition reflects the evolution of BI and its technologies from decision support systems (DSS) and its relations with data warehouses, executive information systems [24].

The principal tools for BI include software for database query and reporting (e.g. SAP ERP, Oracle ERP, etc.), tools for multidimensional data analysis (e.g. OLAP), andDM e.g. predictive analysis, text mining, web mining [25]. DM is also considered as afoundation of BI [11].

However, what intelligence means in BI is still a big issue for comprehending BI. Inwhat follows, this section addresses this issue through exploring temporality, expectability and relativity of intelligence in BI.

Terminologically, intelligence in BI should be at least human intelligence in relationwith business. This kind of intelligence is based on learning and understanding the facts provided by business data, information and knowledge about a business operation andenvironment or a product or service [19]. The ability of learning, understanding and reasoning belongs to the category of human intelligence [26].

The term “intelligent” has been popular, not only in academia but also in the wider community, due to a long time, ongoing research and development of artificial intelligence (AI) and intelligent systems (IS) since 1955 [27]. There are about 243 million results related to "intelligent" in the Google world (searched on 27 May 2016). In the academia, the term "intelligent" frequently appears in titles of a great number ofbooks, book chapters, papers, and international conferences as well as other media or products. In the wider community, the term "intelligent" often appears in homeappliances and customer electronics including televisions, cameras, vacuum cleaners, washing machines [7], and mobile phones, to name a few. Defining intelligent is not asimple task. According to the Macmillan Dictionary [28, p. 787], the term intelligencemeans "the ability to understand and think about things, and to gain and use knowledge". Similarly, the term intelligence has been defined in IS as "the ability to learn and understand, solve problems and make decision" [29, p. 18]. The term intelligent means to be able to perceive, understand, think, learn, predict and manipulate a system [27, p. 1]. All these definitions on intelligence are mainly human intelligence,which has impacted the development of AI [27]. AI has been focusing on intelligence of machines or machine intelligence (Note that the web is also a machine.). In other words, AI is the science and engineering of making intelligent machines to imitate human intelligence [26]. However, a system may not be considered intelligent, even ifit has these abilities associated with human intelligence, because the term intelligent implies some expectations from human beings or society, in particular in the setting ofbusiness. Practically, it appears that an intelligent system contains a set of functions that jointly make the system easy to use [30], because 'easy' is a term related to humanintelligence. More generally, a system or a product is intelligent if and only if it contains a set of functions that jointly make the system either easier or faster, or friendlier, or more efficient, or more satisfactory to use than an existing cognate system taking into account the time. Easier, faster, friendlier, or more efficient, or more satisfactory are allthe expectations of humans or customers or society for the performance of a system orproduct. For example, a high speed train running in China is intelligent, because it is faster and friendlier than the existing ones; these are what the Chinese expect.

The above discussion leads to three perspectives on "intelligence" in BI: Temporality of intelligence, expectability of intelligence, and relativity of intelligence. **Temporality of intelligence**. There are two meanings for temporal intelligence. 1.

Temporal intelligence is the ability to adapt to change. This has been motivated todevelop temporal logic and evolutionary computing including genetic algorithms [27].

2. Temporality of intelligence means that intelligence is related or limited to a time interval. For example, at the time of writing this paper, few people consider floppy disks as intelligent storage devices. However, a few decades ago floppy disks were considered intelligent in comparison to paper tape for data storage. In what follows, welimit ourselves to the meaning of item 2.

Expectability of intelligence. Intelligence can be considered as a substitution for easier, or faster, or friendlier, or more efficient, or more satisfactory. This is expectability of intelligence. We denote them using the degree of satisfaction. All theserelated concepts are a set of expectations of humans, as parts of human intelligence. Wedenote these expectations for a product, P, as $EP =$ $\{e_i \mid e_i \text{ is an expected performance for function}_i \text{ of a product } \} = \{e_i \mid i \in \{1, 2, \dots, n-1, n\}$, where n is a given integer. For every $i \in \{1, 2, \dots, n-1, n\}$, there is a perceived performance of customer for *function*$_i$, p_i, then a product P is intelligent ifand only if there exists at least one $i \in \{1, 2, \dots, n-1, n\}$ such that [31, p. 436]

$$s_i = \frac{p_i}{e_i} \geq 0 \tag{3}$$

where s_i is the satisfaction degree of the customer to the i^{th} function of product P.

For example, an iPhone 6S's Touch ID, Apple's fingerprint recognition feature, is noticeably quicker when unlocking the phone. "quicker" is what the user perceived, $p_1 = 1.5$, while "quick" is an expected performance, $e_1 = 1$, for iPhone 6S from acustomer, based on Equation (3), we have the satisfaction degree of the customer $s_i = 1.5 > 0$. Then an iPhone 6S is intelligent.

Relativity of intelligence. Intelligence is a consequence of comparison between twosystems (or products or services), which leads to the relativity of intelligence. Generallyspeaking, let X and Y be two systems. X is intelligent if X is better than Y with respect to E, where E is a set of human expectations. "Better" is a relativity concept. For example, a new microwave is intelligent because it displays the temperature when microwaving food. A user believes that displaying the temperature is better than not displaying it. This example reflects the relativity of intelligence. Displaying temperature belongs to the set of expectations E. The set of human expectations can be considered as a set of demands. The expectation of human beings and society promotesintelligence and social development. Therefore, it is significant to define IS with respectto the set of human expectations or demands.

In summary, intelligence in BI can be measured through three dimensions: temporality, expectability and relativity. In other words, in a BI system there are threecharacteristics of its intelligence: temporality, expectability and relativity. The degree of intelligence of a BI system or product or service can be measured using this triad, that is,

Degree of intelligence = temporality+ expectability+relativity (4)

Equation (4) is more useful for BI and big data intelligence, because they are based onperformance, business advantages, competiveness advantages of systems or products or services. All of these are closely associated with temporality, expectability and relativity of intelligence. This formula can be realized by using big data analytics and big data, in other words, big data and big data analytics can generate big data intelligence, for short,

big data intelligence = big data +big data analytics (5)

Equation (5) indicates that increase of either big data or big data analytics can increase big data intelligence. This is partially proved by what Professor Peter Norvig,the Google's Director of Research, said "we don't have better algorithms; we just havebig data" [4].

Temporality, expectability, relativity of intelligence can be considered as a fundamental for BI including organization intelligence, enterprise intelligence, marketing intelligence [14] and big data intelligence. We will explore it as a future work.

In fact, the global competitiveness among the giant companies lies in these three dimensions of intelligence in businesses, decision making, products and systems. Big data and analytics will intensify the competition of the giant companies in terms of temporality, expectability, relativity of intelligence. This might be a reason why giant companies are adopting big data and analytics technologies [3, 32]. This degree of intelligence also differentiates BI from AI using the three properties of intelligence in BI. Throughout this paper, we use these three dimensions of intelligence as the basis tounderstand BI.

Big data analytics can be considered as a part of BI [11, 25], because it "supports business decision making with valuable data, information and knowledge" [6]. Both BIand big data analytics are common in emphasizing either valuable data or informationor knowledge. Tableau [3], QlikView and Tibco's Spotfire are leading BI tools for interactive visualization for data exploration and discovery [32]. These BI tools are also considered as the tools of big data analytics. This implies that BI and big data analytics share some common tools to support business decision making.

Currently, BI is based on four cutting-age technology pillars: cloud, mobile, big dataand social networking technologies [22, 32] (Note that technology as a service is becoming popular in cloud computing). Each of these pillars corresponds to a special kind of web services, that is, cloud services, mobile services, big data services and social networking services. All these constitute modern web services, the Internet of services [23]. Each of these services has been supported by big data analytics services[6, 7], as shown in Figure 2. This may be the reason why many companies have been moving from BI, DM, and DW to business analytics in general and big data analytics (BA) in specific in recent years [26, 3].

It should be noted that for the state-of-art web services, Sun et al [23, 7] explores that web services mainly consist of mobile services, analytics services, cloud services,social networking services, and service as a web service. Here we emphasize big data analytics services at the center to support cloud services, social networking services, mobile services, and e-services to reflect the big data and big data analytics as an emerging new service [7].

Based on IDC's prediction for the IT market in 2014 [33], spending on big data willexplode and grow by 30% to $14+ billion, in which, the spending on big data analyticsservices will exceed $4.5 billion, growing 21%. The number of providers of big data analytics services will triple in three years. This means that big data analytics serviceshave become an important emerging market, together with the Internet of services including e-services, cloud services, mobile services and social networking services. All these five services and the technologies shape the most important markets for e- commerce and e-business [23].

Discovering information, knowledge and wisdom from databases, data warehouses, data marts and the Web is not only a central topic for business operations, marketing and BI [7], big data analytics can also use it to measuretemporality, expectability and relativity of intelligence of BI for improving business decision making.

BASOA: Big Data Analytics Service Oriented Architecture

This section proposes a big data analytics service-oriented architecture (BASOA) andthen examines each of the main players in the BASOA.

Different from the traditional SOA [34], the proposed BASOA specifies general services to big data analytics services, as showing in Figure 3. We use BA (big analytics) in this architecture, BASOA, to represent big data analytics. This is reasonable because big data and big analytics both are originally from data and analytics respectively [16, 7].

In this BASOA, big data analytics service provider, big analytics service requestor,big data analytics service broker are three main players. In what follows, we will look at each of these in some detail, taking BI into account.

In BASOA, big data analytics service requestors include organizations, governmentsand all level business decision makers such as CEO, CIO and CFO as well as managers.Big data analytics service requestors also include business information systems and e-commerce systems. Big data analytics service requestors require big data analytics services including information analytics services, knowledge analytics services, organization analytics services, business analytics services, market analytics services with visualization techniques to provide knowledge patterns and information as well aswisdom [19] for decision making in the form of figures or tables or reports [35]. Moregenerally, big data analytics service requestors include people who like to make decisions or acquire information based on analytical reports provided by big data analytics service provider [6]. Therefore, a person with smartphone receiving analyticsservices like GPS information is also a big data analytics service requestor [17, 7].

Applying BASOA to Enhance BI

This section looks at how to apply the proposed BASOA to enhance BI in some detail.BAaaS (Big data analytics as a service), as discussed in the BASOA above, means that an individual or organization or information system or software agent uses a widerange of analytic tools or apps wherever they may be located [17]. BAaaS has theability to turn a general analytic platform into a shared utility for an enterprise ororganization with visualized analytic services [17]. A big data analytics service can beavailable on the Web or used by smartphone [7]. Therefore, big data analytics servicesinclude e-analytics services or web analytics services (WAS) and Amazon WebServices (AWS) [6, 3]. Furthermore, big data analytics services also include businessanalytics services, marketing analytics services, organizational analytics services, security analytics services and predictive analytics services [5]. Big data analyticsservices are gaining popularity rapidly in business, e-commerce, e-service, andmanagement in recent years. For example, big data analytics services model has been adopted by many famous web companies such as Amazon, Microsoft, and eBay [17].The key reason behind it is that the traditional hub-and-spoke architectures cannot meetthe demands driven by increasingly complex business analytics [17]. BAaaS promises to provide decision makers with visualizing much needed big data [7]. Cloud analyticsis an emerging alternative solution for big data analytics [6].

As previously defined, BI is a set of theories, methodologies, architectures, systemsand technologies that support business decision making with valuable data, informationand knowledge". BASOA is an architecture for supporting business decision making with big data analytics services. The theory of big data analytics providers, brokers andrequestors of the BASOA can facilitate the understanding and development of BI and business decision making. For example, from an in-depth study of the BASOA, an enterprise and its CEO can know who are the best big data analytics providers and brokers in order to improve his organization, business, market performance, and globalcompetitiveness.

We surveyed 71 information technology managers at the Association for Educationin Journalism and Mass Communication (AEJMC) in Montreal during August 6-9, 2014 [6], to collect data concerning the enterprise-level acceptability of the BASOA concept. These results indicate some preliminary support for the BASOA concept of having service brokers work with service requesters and providers similar to the way private mortgage and loans work in the USA. Based on this preliminary enterprise acceptability of this BASOA model, we propose that more research be done toinvestigate how it could be used in the near future.

Related Work and Discussion

We have mentioned a number of scholarly researches on data analytics, big data analytics, and BI. In what follows, we will focus on related work and discussion on ontology of big data analytics, and the work of SAP as well as incorporation of big dataanalytics into BI.

Why does big data analytics really matter for modern business organizations? Thereare many different answers to this question from different researchers. For example, Davis considers that the current big data analytics has embodied the state-of-artdevelopment of modern computing [38], which has been reflected in Section 2.Gandomi and Harder [14] discuss how big data analytics has captured the attention of business and government leaders through decomposing big data analytics into text analytics, audio analytics, video analytics, social media analytics, and predictiveanalytics. This implies that big data can be classified into big text data, big audio data,big video data, and big social media data [14].

Big data analytics and BI have drawn an increasing attention in the computing, business, and e-commerce community recently. For example, Lim et al [11] examine BI and analytics by focusing on the research directions. They consider BI and analytics(BIA) as a current form replacing the traditional BI, whereas we still consider BI and big data analytics are two different concepts, although they have close relationships andshare some commons.

One of the contributions of this paper is that big data analytics services can enhance BI. Fan et al [14] provide a marketing mix framework for big data management through identifying the big data sources, methods, and applications for each of the marketing mix, consisting of people, product, place, price and promotion. However, they have not shown the relationship between marketing intelligence and BI in terms of big data analytics.

II. Conclusion

This paper examined how to use big data analytics services to enhance BI by presentingan ontology of big data analytics and a big data analytics service-oriented architecture(BASOA), and then applying BASOA to BI, where our surveyed data analysis showed that the proposed BASOA is viable for enhancing BI and enterprise information systems. This paper also examined temporality, expectability and relativity as the characteristics of intelligence in BI, and discussed the interrelationship between BI andbig data analytics. The proposed approach in this paper might facilitate the research anddevelopment of business analytics, big data analytics, BI, e-services and IoS as well asbig data computing and big data science.

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