



Application of Big Data Analytics in the Smart Building Projects.

Sameer Jain¹

Dr.Devendra Kumar Punia²

Abstract

The studies for smart environments and in particular, smart buildings are slowly becoming a reality, with installations starting to spread all around the world. Smart offices, smart factories, and smart housing, especially social housing, are nowadays giving a new impulse to research, with new needs and issues to tackle. Among the several problematic stemming from such a wide deployment of these technologies, Big Data issues are currently gaining a new momentum: while installation grow and start covering large-scale settings with hundreds or thousands of installed sensors and actuators, data granularity, frequency, scalability, and cardinality issues are increasingly attracting research efforts.

Introduction

Building an effective business case for a Big Data project involves identifying several key elements that can be tied directly to a business process and are easy to understand as well as quantify. These elements are knowledge discovery, actionable information, short- term and long-term benefits, the resolution of pain points, and several others that are aligned with making a business process better by providing insight.

Big Data research is already facing similar issues, aiming at effectively handling, processing, and delivering high-cardinality and/or high-throughput streams of data stemming from several sources, be they blogs/tweets/Internet sensors, or measures



extracted from a smart building, Smart buildings, in effect, are a highly demanding test environment for Big Data technologies as almost all of the most important issues are present. In a smart building, say a smart factory, data are typically delivered at high rates, with single event delivery at intervals often much lower than a second. Data granularity is diverse, as sensors on the field operate on different time frames, for example, process control sensors work on milliseconds time scales, whereas energy metering usually operate operates on a minute or hour scale.

While that might sound like a real challenge, businesses are actually investing in storage technologies and improved processing to meet other business goals, such as compliance, data archiving, cloud initiatives, and continuity planning. These initiatives can provide the foundation for a Big Data project, thanks to the two primary needs of Big Data: Storage and processing.

Building a business case involves using case scenarios and providing supporting information. An extensive supply of examples exists, with several draft business cases, case scenarios, and other collateral, all courtesy of the major vendors involved with Big Data Solutions. Notable vendors with massive amounts of collateral include IBM, Oracle and HP.

While there is no set formula for building a business case, there are some critical elements that can be used to define how a business case should look, which helps to ensure the success of a Big Data Project.



Data Sourcing

Many industries fall under the umbrella of new data creation and digitization of existing data, and most are becoming appropriate sources for Big Data resources. Those industries include the following:

- Transportation, logistics retail, utilities, and telecommunication. Sensor data are being generated at an accelerating rate from fleet GPS transceivers, RFID(radio-frequency identification) tag readers, smart meters and cell phones (call data records), these data are used to optimize operations and drive operational BI to realize immediate business opportunities.
- Health Care: The health care industry is quickly moving to electronic medical records and images, which it wants to use for short-term public health monitoring and long-term epidemiological research programs.
- Government. Many government agencies are digitizing public records, such as census information, energy usage, budgets, Freedom of Information Act documents, electoral data, and law enforcement reporting.
- Entertainment media: The entertainment industry has moved to digital recording, production, and delivery in the past five years and is a now collecting large amount of rich content and user viewing behaviors.
- Life sciences: Low cost gene sequencing (less than \$1,000) can generate tens of terabytes of information that must be analyzed to look for genetic variations and potential treatment effectiveness.
- Video surveillance: Video surveillance is still transitioning from closed-caption television to internet protocol television cameras and recording systems that organizations want to analyze for behavioral patterns (security and service enhancement).



Application Areas

Numerous functions within a business can benefit from analytics. The most common functional categories include:

- 1) *Customer analytics*: This category includes applications to marketing (customer profiling, segmentation, social network analysis, brand reputation analysis, marketing mix optimization) and customer experience.
- 2) *Supply chain analytics (SCA)*: This includes demand forecasting and optimization of inventory, pricing, scheduling, transportation, and storage, while mitigating and risk. A branch of SCA, human capital analytics aka workforce analytics, relates to service industries where human resources are the foremost means of production.
- 3) *Analytics in public domain*: Driven by natural resource constraints, governments are using analytics for tasks such as detecting water leakages in distribution systems, making energy grids and traffic systems smarter, and improving public safety.
- 4) *Fraud and risk analytics*: This includes assessment of various types of risk (market, operational, credit) mostly in the financial sector.

Degree of Complexity

Complexity of analytics can be broken down into three layers: descriptive analytics, predictive analytics and prescriptive analytics.

- 1) **Descriptive Analytics:** Several businesses start with descriptive analytics to analyze business performance. Descriptive analytics analyze historical data and identifies partners from samples for reporting of trends. Techniques such as data modeling, visualization, and regression analysis are most common in this analytics:

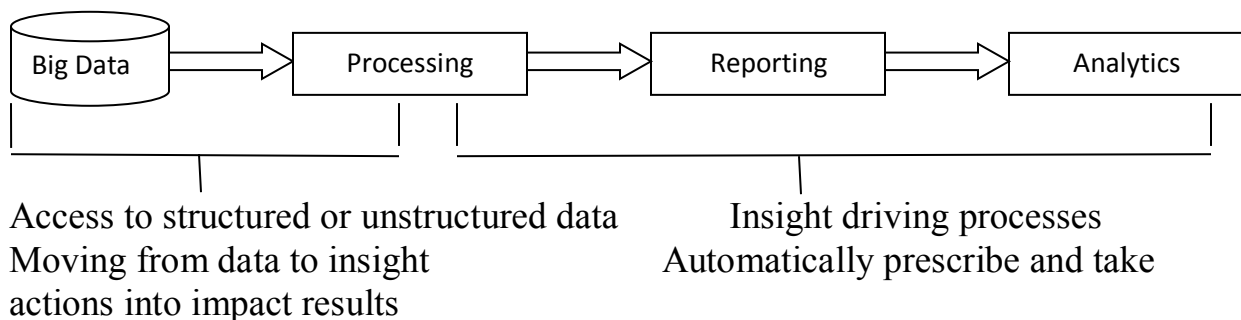


Fig1: The Analytics value chain

Descriptive analytics can be classified into following tasks:

- *Usual reporting and dashboards:* What took place? How does it relate to our blueprint?
- *Adhoc reporting:* How many? Where?
- *Analysis/query:* What exactly is the challenge? Why is this happening?

Descriptive analytics are the commonly used and well-understood type of analytics. It basically categorizes, characterizes, consolidates, and classifies data. Tools for descriptive analytics may provide mechanisms for interfacing to enterprise data sources. They contain report generation, distribution capability, and data visualization facilities. Descriptive analytic techniques are mostly applied to

structured data, although there have been attempts to extend to unstructured data, through the structured metadata and indices.

- 2) **Predictive Analytics:** Predictive analytics use data to find out what could happen in the future. It is a more refined and higher level usage of analytics. It predicts future probabilities and trends and finds relationships in data not instantly apparent with traditional analysis. Data mining and predictive modeling tools and techniques are being used in this kind of analytics.

Predictive analytics can be classified into six tasks:

- *Data mining:* What data are correlated with other data?
- *Forecasting:* What revenue will we close our annual balance sheet with?
- *Root cause analysis:* Why did it occur?
- *Pattern recognition:* When should we alter a process?
- *Monte-Carlo simulation:* What could emerge?
- *Predictive modeling:* What will happen then?

Predictive analysis applies sophisticated techniques to investigate scenarios and helps one to detect hidden patterns in large quantities of data in order to project forthcoming events. It uses techniques that segment and group data into comprehensible sets in order to predict behavior and detect trends. It utilizes clustering, rules, decision trees, and even neural network tools and techniques.

- 3) **Prescriptive Analytics:** Once the past is understood and predictions can be made about what might happens in the future, one need to know what the best action will be, given the limited resources of the enterprise. This is the area of perspective analytics, respective analytics use data to propose the best course of action to increase the chances of realizing the finest outcome. Optimization and simulation techniques are being used for this kind of



analytics. Prescriptive analytics are based on the concept of optimization, which can be divided into two areas.

- *Optimization*: How can we achieve the best results?
- *Stochastic optimization*: How can we achieve the best result and tackle improbability in the data to make better decisions?

Examples of Analytic technologies

Smart Cities

Cities of today are confronting massive urbanization challenges that can threaten long-term sustainability. These challenges can affect the city's economy businesses, and people and can encompass core infrastructures such as traffic, water energy, and communication. A “smart city” makes optimal use of all interconnected information available today to better understand and control its operations and optimize the use of limited resources. At this point, we highlight some key domains that play an important role in a city.

The basic conflict between population increase and availability of fresh water leads to increasing concerns over water quality, failing water infrastructures, and overall water management complexity. IT and analytics can help deliver solutions to numerous water-related issues that are currently handled inadequately by inefficient and often manual processes. For example noninvasive leakage detection is possible using optimization algorithms at the network level, by detecting anomalies between modeled performance and actual sensor readings.



Congested transportation systems deter economic activity, waste energy, and emit significant amounts of carbon into the atmosphere. Traditional approaches that increase the size of the underlying infrastructure are beginning to hit a wall because it is economically and environmentally unsustainable. Smarter traffic systems take advantage of technology and collect physical data about urban traffic and mobility patterns. These data can help traffic management centers analyze and make better decisions regarding road network management, toll road practices, and public transit services.

Conclusions: Big Data Analytics is emerging as an important and useful tool for organizations to validate and answer business questions, it is essential to note that Big Data Analytics can at best be an effective supporting tool if it is aligned with the overall organization business strategy. In this, we understood that society evolves at the same pace of the web, online social data are becoming increasingly important for both individuals and businesses. In order to reduce such complexity, we need to adopt a multidisciplinary approach to big social data analysis, which combines different perspectives by means of social network analysis, multimedia management, and more. There is a strong need to handle unstructured data in segments such as Operational/Service Analytics and Marketing/Customer Analytics. The analyst analyzes various heterogeneous data sources enabled by advanced analytical capabilities such as data linking, text clustering, text annotation, sentiment mining, and predictive modeling, to come up with actionable insights regarding customer churn, key customer satisfaction and dissatisfaction drivers.



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