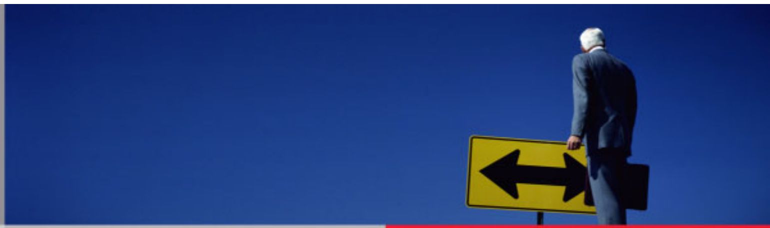
Analytics in a Big Data Environment



Redguides
for Business Leaders

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Robert Ames

- Learn strategies to make sense of your data
- Explore technologies that are used to gather intelligence
- Take a look at the future of analytics

Introduction

The intelligence community is facing a grand analytics challenge. The volume, velocity, and variety of data are growing exponentially, and the *needle-in-the-haystack* problem threatens to become significantly worse. Whether an organization wants to better detect enemies, protect its infrastructure from cyber terrorism, or formalize its understanding of a situation, it uses analytics to help make sense of the available information and choose an appropriate action. As adversaries adopt new methods, analytic systems must evolve to stay one step ahead of them. To succeed, organizations must embrace and use the power of the volume, velocity, and variety of data, rather than being overwhelmed by it.

Through analytics, organizations can discover patterns and relationships that enable better decision making. Smart business decisions demand that these discoveries are made within the right context, which is called *situational awareness*. Organizations gather data and use internal relevance-detection and situational assessment algorithms to assess the data, and alert us on the arrival of a high interest observation. Without context, misguided findings result in poor decisions and non-competitive offerings in the marketplace. For government, they can result in wasted resources, misdirected aggression, and unforeseen attacks on society. In many cases, these issues result from too little data, not too much data.

Experience shows that traditional analytic systems are challenged as data becomes bigger, faster, and increasingly unstructured. Recent technology innovations allows organizations to use all their data, in near real time, to provide accurate and timely analysis. The analytic process becomes more accurate (reduction of false positive and false negatives) when there is more data. Analytic model accuracy is further enhanced by adding a rich and correct cumulative context.

Humans perform complex analytics daily. As an example, they analyze traffic patterns many times each day and decide when to cross intersections. This situation is complex, with moving actors and a highly dynamic environment. Situational awareness implies an understanding of relevant history (car behavior and speed), learned behavior (look left, right, and left), knowledge of traffic laws, and the current environment (number of cars and speed of cars). This situational data can help people decide how a new event, such as crossing a street, will impact the objective of staying safe. Imagine making these decisions based on five-minute old data, rather than real-time data. New analytic capabilities can enable computing systems to augment human decision making and help over-burdened analysts cope with the inevitable crush of data.

Better, more accurate decisions can be generated when all of the available data is used to create a persistent context. Context serves as a "ground truth" of understanding, offering a current description of the entities that are relevant to the decision analytics (people, organizations, and connections between the entities and events).

This IBM® Redguides™ publication introduces ideas and concepts that IBM Research is exploring about deriving information and knowledge from data. This guide provides examples of using these concepts to effectively analyze and fuse seemingly unrelated data, helping analysts to make well-informed decisions. In addition, this guide highlights key technologies that IBM Research is exploring and takes a glimpse of the future.

Big data analytics

Big data analytics require a layered technology deck (illustrated in Figure 1) because data varies in volume, variety (structured and unstructured), and velocity (streams where data flows over constantly running queries).

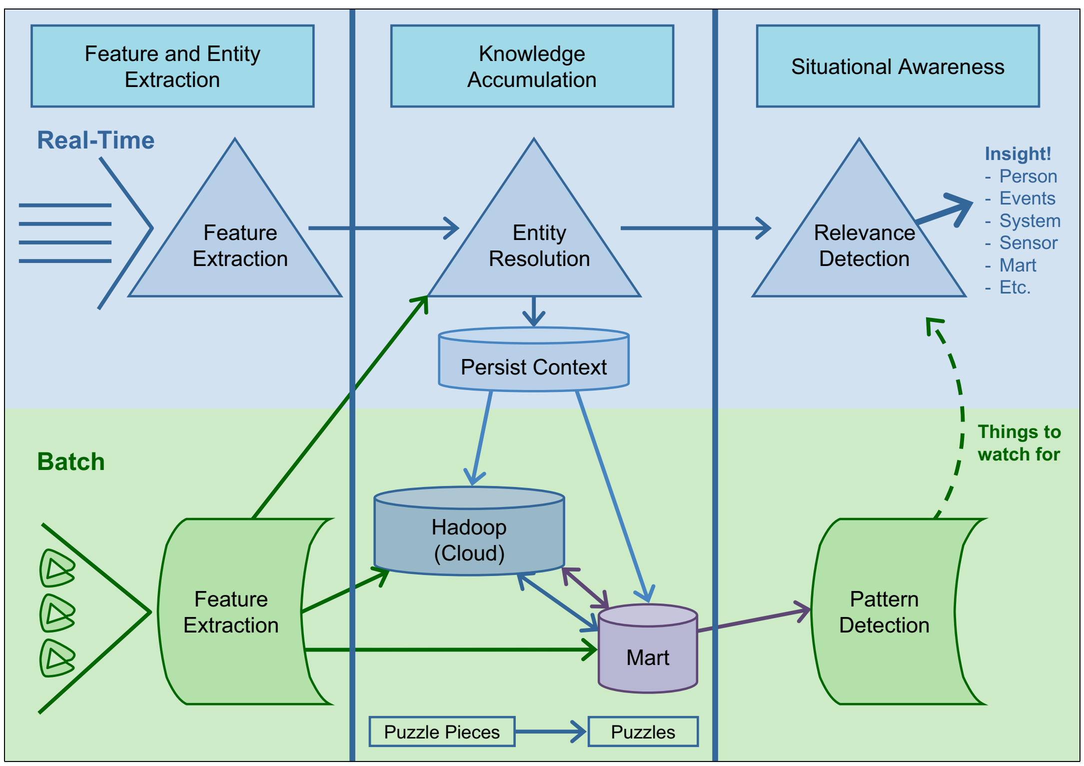

Figure 1 Layered technology for big data analytics

Two new key technologies enable computing infrastructure, Hadoop MapReduce and Streams (stream computing). When these new infrastructures are combined with traditional enterprise data marts, analytics can use the full range of data. Persistent context glues the environments together. Hadoop enables redesigned analytics to quickly ingest and use enormous data sets, and to combine data that previously was impossible to bring together, due to the rigidity of traditional database schemas. The ability of Hadoop to use all of the data reduces the chance of missing low-level anomalies within predictive models. Models embedded in streams can assess the relevance of each new data element on arrival. Analytic accuracy, including the reduction in false positives and false negatives, is enhanced through the use of a context-based historical data set.

Persistent context can be used to identify emergent patterns within the data, such as patterns of life, and anomalies in the data. The combination of streams and persistent context allows for the real-time assessment of each new data for cumulative relevance or contributions to models such as threat scores.

Hadoop and Streams: For more information about Apache Hadoop, see the What is Hadoop page at:

http://www.ibm.com/software/data/infosphere/hadoop/

For more information about stream computing, see the IBM Stream Computing page at:

http://www.ibm.com/software/data/infosphere/stream-computing/

The following key technologies, among others, are vital to ensure effective intelligence:

- Feature extraction
- Context and situational awareness
- Predictive modeling
- Data analysis upon arrival

In most cases, these technologies have existed for some time, but are now enjoying much greater scale and performance due to new computing capabilities and architectures. When looked at individually, each is powerful. If you can envision using them collectively, the opportunity is vast.

Feature extraction

Analytics requires relevant structured data. Unstructured data requires work to extract relevant information. To facilitate extraction on enormous amounts of text data, IBM Research created a scalable, high performing rule-based extraction system with a higher level language, similar to SQL. This extraction system is less domain specific to abstract the complexity of the underlying compute environment and to ease the text analytics challenge. This IBM Research tool, known as *SystemT*, runs on top of Hadoop. System T can automatically extract structured information. For example, PERSON has PHONE, COMPANY1 acquired COMPANY2 on DATE. Alternatively, SystemT can extract more complex concepts such as sentiment from various unstructured or semistructured sources such as blogs or text documents. A persistent context engine can use the extracted data.

Context and situational awareness

An organization is only as intelligent as its ability to use analytics to make sense of data about relevant events and entities in terms of strategic, operational, or tactical goals. Data comes in the form of observations collected across various enterprise sensors, such as transactional systems and open source data. However, more data does not necessarily mean more intelligence. Intelligence comes from ability to understand and use the current context.

Effective analytics require detailed and aggregated data, for example, about people, places, things, and organizations. If the detailed data is not associated with the correct entity, the analytical calculations are incorrect. As an example of an entity normalization problem, consider that banks must report cash transactions over $10,000. A bank might have ten $5,000 cash transactions. It must determine whether these transactions involve ten people, each with $5,000, or one person with $50,000. The determination that the individuals described in the two banking transactions are the same person is an *assertion*. Without clear and current assertions about entities, decisions will be inaccurate and opportunities will be missed.

Observations have two important (and sometimes overlapping) aspects:

- Identity data
- Event data

In general, the amount of data associated with different identities is small and slowly evolving when compared to the data about their events or behaviors. Most people, even those people who seek to hide themselves, have a limited number of identities. In contrast, the actions taken by those entities occur constantly, have a far more dynamic nature, and can be discovered by different sensors. As an example, consider that the social network of an individual shifts constantly through events, but the individual's identity remains fixed.

Creating the data environment for modeling: Predictive modeling

Consider the scenario where a mega bank acquires new banks and wants to create a special refinancing promotion for good customers. The mega bank wants to create an updated loan scoring model that uses historical data about loans for customers (entities) and about past loans (events) within multiple data silos. Some customers have accounts in multiple banks. If all customers used their real names and addresses consistently, and provided all details comprehensively and unambiguously, the grouping of data for each individual might be trivial. In most circumstances, the data needed for resolution is incomplete and ambiguous. Further, this data is in diverse data sources for different operational activities that share few overlapping fields.

Accurate loan models determine the likelihood of an individual to pay back a loan and are based on previous loan histories, such as the amount and the payback interval. If an individual has multiple loans, the predictive model must assess that individual's complete history. If the identity information is inconsistent, the scoring algorithm considers each loan separately, rather than assessing the customer's ability to pay back all outstanding loans. In this scenario, the data is available, but proper context required for effective decision making is not available. Without context and normalization, analytic models are inaccurate and misleading.

The traditional solution is to merge the data by using primary keys, such as name and social security number (SSN). Data that lacks primary keys (no consistent and unique key to link the same individual across different banks) cannot be merged. The example in Figure 2 does not have a single primary SSN key. Therefore, the records remain unmerged. Entity 649 seems to be a great loan candidate with one small existing loan and no current defaults.

Bank 1 – Entity 105	
Name	Louise Doe
	L.D. Doe
Addr	123 Main Street
	777 Park Road
City	New York
State	NY
Postal	11732
SSN	123-45-678
Loan#	$100,000
Default	Yes

Bank 2 – Entity 349	
Full	Jane Doe
Addr1	33 Red Dr
City	Mamaroneck
State	NY
Postal	10354
SSN	123-45-678
Phone	914-555-1212
Loan#	$150,000
Default	Yes

Bank 3 – Entity 649	
Full	Jane Doe
Addr1	33 Reed Dr
City	White Plains
State	NY
Postal	10354
Phone	914-555-1212
Loan#	$10,000
Default	No

Figure 2 Sample bank data

In contrast, entity normalization can discover nonobvious relationships and reveal that Customer 649 has multiple outstanding loans.

Figure 3 illustrates how common attributes across diverse records can help to identify nonobvious relationships. The three individual rows within the data set can now be collapsed to one single row or entity. Of particular interest is the Loan variable, which is summed over the three entities. Entity 649 is not as good a loan candidate as initially thought. Predictive models that use normalized data as a basis generate a more accurate predictive model. Scoring models that have a more accurate view of the individual create a more accurate score.

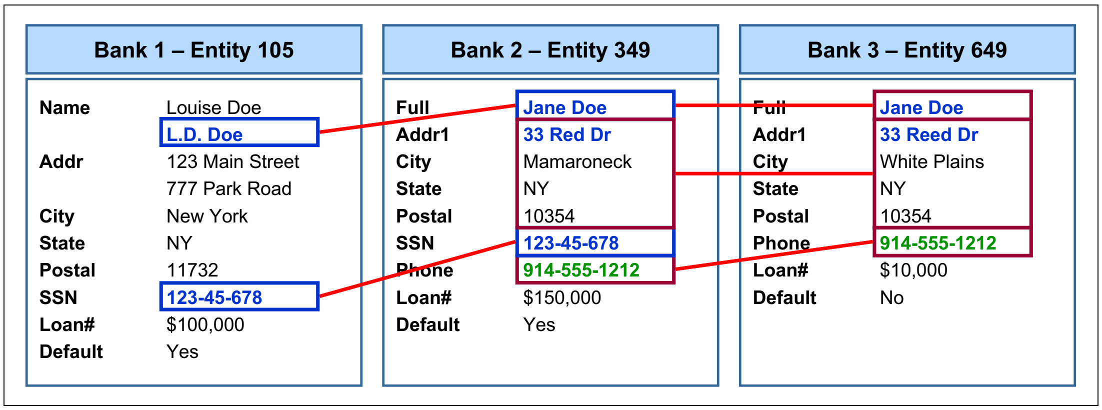

Figure 3 Identifying nonobvious relationships

This scenario illustrates the power of persistent context and its positive impact on predictive models. The fusion of the orthogonal data sources (shown in Figure 4) revealed much more information about entities and helps to avoid making bad decisions with good data. In addition, as predictive model accuracy increases, you see an important reduction in false positives and negatives, meaning that you can find more needles in bigger haystacks.

Name	Louise Doe Jane Doe LD Doe
Addr1	123 Main Street 777 Park Road 33 Red Dr 33 Reed Dr
City	New York, White Plains, Mamaroneck
State	NY
Postal	11732, 10354
SSN	123-45-678
Phone	914-555-1212
Loans	$260,000
Defaults	Yes

Figure 4 Fused data

Predictive modeling on large amounts of data

Application and computer memory limitations previously dictated the use of sampling techniques when creating predictive models. However, sampling reduces the likelihood of detecting anomalies and rare events.

Internet scale analytics have driven the development of new analytic platform architectures. Hadoop and MapReduce provide a simple, but powerful framework, for parallel analytics. Complex, high computation per record analytics, such as the IBM SPSS® software predictive modeling, can take advantage of the inherent scalability of Hadoop. Examples of SPSS predictive modeling include clustering, latent factor analysis, decision tree, neural nets, and linear regression. In addition, topic analysis, video scene analysis, and semantic analysis of text can use the scalability that Hadoop provides.

Organizations can now run large, complex analytics on a large volume of data by starting subcomponents or tasks on multiple servers in parallel. What previously was too costly is now possible and relatively easy to implement.

Assessing the value of each piece of data on arrival

Analytics need to make sense of the world as observations present themselves. Analytics must do this analysis fast enough to take action on this information when the observations are happening. A new observation can expand known identity information (for example, an alias), discover a new relationship, or identify surprising and relevant events and insights. Arriving data can be assessed against models that describe trends, sentiments, behaviors, and more. The assessment must be fast and have the capacity to scale with ever-increasing volumes of data. It must be able to handle the purposeful obfuscation of information that is inherent in intelligence data sources. It must also be linguistically aware to accommodate the many languages that comprise intelligence collections.

Streaming analytic frameworks enable analysts to apply various continuous and predictive analytics to structured data and unstructured data in motion. They bring high value information in near real time, rather than waiting to store and perform traditional business intelligence operations that might be too late to affect situational awareness.

The future

New and emerging technologies enable analytics to use the volume, velocity, and variety of data, rather than being overwhelmed by them. These new approaches to computation make analytics possible (that were previously thought impossible) and make them affordable. The future will continue to deliver more sophisticated techniques to big data analytics.

IBM Watson™ (a question-answering system), most recently used to play Jeopardy!, can be used to automate hypothesis generation and related investigations to gather and present new evidence to an analyst. For example, it can sift through massive amounts of structured, semi-structured, and unstructured intelligence community information. It can collect evidence for and against a hypothesis and present it with supporting information and confidence ranking.

These technologies must be investigated fully to derive meaningful intelligence from the oncoming wave of data that is created daily and promises to grow exponentially. The volume, velocity, and variety of data pose a significant challenge, but offer a tremendous opportunity to expand enterprise knowledge, bringing new efficiencies, greater safety, and the promise of a smarter planet toward reality.

Other resources for more information

For more information about the topics mentioned in the paper, go to the following web pages:

- IBM InfoSphere® platform

  http://www.ibm.com/software/data/infosphere/

- Big data analytics

  http://www.ibm.com/software/data/infosphere/bigdata-analytics.html

- IBM SPSS software

  http://www.ibm.com/software/analytics/spss/

- IBM Watson

  http://www.ibm.com/innovation/us/watson/index.html

- IBM DeepQA Project

  http://www.research.ibm.com/deepqa/deepqa.shtml

- SystemT project

  http://www.almaden.ibm.com/cs/projects/systemt/

- *SystemT: A System for Declarative Information Extraction*

  http://www.almaden.ibm.com/cs/people/yunyaoli/publication/sigmodRecord2009.pdf

The team who wrote this guide

This content in this guide was adapted from the original version published in *IQT QUARTERLY* in the Spring 2011 edition. The authors of both versions worked with the IBM International Technical Support Organization (ITSO) to provide this publication.

Dr. Lisa Sokol is an architect within the IBM Government Services CTO office. Her primary areas of interest are assisting government communities in dealing with the decision overload problem and using analytics to discover actionable information buried within large amounts of data. She has designed several systems that detect and assess threat risk relative to fraud, terrorism, counter intelligence, and criminal activity. She has a doctorate in Operations Research from the University of Massachusetts.

Robert Ames was, at the time this guide was written, the Director of Advanced Analytics and Big Data at IBM. In this capacity, he advised senior leaders and technologists across the government who were grappling with its biggest challenges. Robert worked to ensure that the unique needs of the government were reflected in the activities of IBM Research and Development. He also worked to ensure effective collaboration between the government, its partners, and IBM in delivering advanced technologies to the mission.

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