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DRAFT NIST Big Data Interoperability Framework:
Volume 6, Reference Architecture

NIST Big Data Public Working Group
Reference Architecture Subgroup

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NIST Big Data Public Working Group (NBD-PWG)
Reference Architecture Subgroup
National Institute of Standards and Technology
Gaithersburg, MD 20899

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Reports on Computer Systems Technology

The Information Technology Laboratory (ITL) at NIST promotes the U.S. economy and public welfare by providing technical leadership for the Nation's measurement and standards infrastructure. ITL develops tests, test methods, reference data, proof of concept implementations, and technical analyses to advance the development and productive use of information technology. ITL's responsibilities include the development of management, administrative, technical, and physical standards and guidelines for the cost-effective security and privacy of other than national security-related information in Federal information systems. This document reports on ITL's research, guidance, and outreach efforts in Information Technology and its collaborative activities with industry, government, and academic organizations.

Abstract

Big Data is a term used to describe the large amount of data in the networked, digitized, sensor-laden, information-driven world. While opportunities exist with Big Data, the data can overwhelm traditional technical approaches and the growth of data is outpacing scientific and technological advances in data analytics. To advance progress in Big Data, the NIST Big Data Public Working Group (NBD-PWG) is working to develop consensus on important, fundamental concepts related to Big Data. The results are reported in the *NIST Big Data Interoperability Framework* series of volumes. This volume, Volume 6, summarizes the work performed by the NBD-PWG to characterize Big Data from an architecture perspective, presents the NIST Big Data Reference Architecture (NBDRA) conceptual model, and discusses the components and fabrics of the NBDRA.

Keywords

Big Data, reference architecture, System Orchestrator, Data Provider, Application Provider, Framework Provider, Data Consumer, Security and Privacy Fabric, Management Fabric, use cases, Big Data characteristics

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The document contains input from members of the NBD-PWG: Reference Architecture Subgroup, led by Orit Levin (Microsoft), Don Krapohl (Augmented Intelligence), and James Ketner (AT&T); Technology Roadmap Subgroup, led by Carl Buffington (Vistronix), David Boyd (InCadence Strategic Solutions), and Dan McClary (Oracle); Definitions and Taxonomies Subgroup, led by Nancy Grady (SAIC), Natasha Balac (SDSC), and Eugene Luster (R2AD); Use Cases and Requirements Subgroup, led by Geoffrey Fox (University of Indiana) and Tsegereda Beyene(Cisco); Security and Privacy Subgroup, led by Arnab Roy (Fujitsu) and Akhil Manchanda (GE).

NIST SP1500-6, Version 1 has been collaboratively authored by the NBD-PWG. As of the date of publication, there are over six hundred NBD-PWG participants from industry, academia, and government. Federal agency participants include the National Archives and Records Administration (NARA), National Aeronautics and Space Administration (NASA), National Science Foundation (NSF), and the U.S. Departments of Agriculture, Commerce, Defense, Energy, Health and Human Services, Homeland Security, Transportation, Treasury, and Veterans Affairs.

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Notice to Readers

NIST is seeking feedback on the proposed working draft of the *NIST Big Data Interoperability Framework: Volume 6, Reference Architecture*. Once public comments are received, compiled, and addressed by the NBD-PWG, and reviewed and approved by NIST internal editorial board, Version 1 of this volume will be published as final. Three versions are planned for this volume, with versions 2 and 3 building on the first. Further explanation of the three planned versions and the information contained therein is included in Section 1.5 of this document.

Please be as specific as possible in any comments or edits to the text. Specific edits include, but are not limited to, changes in the current text, additional text further explaining a topic or explaining a new topic, additional references, or comments about the text, topics, or document organization. These specific edits can be recorded using one of the two following methods.

1. **TRACK CHANGES**: make edits to and comments on the text directly into this Word document using track changes
2. **COMMENT TEMPLATE**: capture specific edits using the Comment Template (http://bigdatawg.nist.gov/_uploadfiles/SP1500-1-to-7_comment_template.docx), which includes space for Section number, page number, comment, and text edits

Submit the edited file from either method 1 or 2 to SP1500comments@nist.gov with the volume number in the subject line (e.g., Edits for Volume 6.)

Please contact Wo Chang (wchang@nist.gov) with any questions about the feedback submission process.

Big Data professionals continue to be welcome to join the NBD-PWG to help craft the work contained in the volumes of the NIST Big Data Interoperability Framework. Additional information about the NBD-PWG can be found at http://bigdatawg.nist.gov.

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Executive Summary

The NIST Big Data Public Working group (NBD-PWG) Reference Architecture Subgroup prepared this *NIST Big Data Interoperability Framework: Volume 6, Reference Architecture* to provide a vendor-neutral, technology- and infrastructure-agnostic conceptual model and examine related issues. The conceptual model, referred to as the NIST Big Data Reference Architecture (NBDRA), was crafted by examining publicly available Big Data architectures representing various approaches and products. Inputs from the other NBD-PWG subgroups were also incorporated into the creation of the NBDRA. It is applicable to a variety of business environments, including tightly-integrated enterprise systems, as well as loosely-coupled vertical industries that rely on cooperation among independent stakeholders. The NBDRA captures the two known Big Data economic value chains: information, where value is created by data collection, integration, analysis, and applying the results to data-driven services; and, the information technology (IT), where value is created by providing networking, infrastructure, platforms, and tools in support of vertical, data-based applications.

The *NIST Big Data Interoperability Framework* consists of seven volumes, each of which addresses a specific key topic, resulting from the work of the NBD-PWG. The seven volumes are as follows:

- Volume 1, Definitions
- Volume 2, Taxonomies
- Volume 3, Use Cases and General Requirements
- Volume 4, Security and Privacy
- Volume 5, Architectures White Paper Survey
- Volume 6, Reference Architecture
- Volume 7, Standards Roadmap

The *NIST Big Data Interoperability Framework* will be released in three versions, which correspond to the three stages of the NBD-PWG work. The three stages aim to achieve the following with respect to the NBDRA:

Stage 1: Identify the high-level Big Data reference architecture key components, which are technology, infrastructure, and vendor agnostic
Stage 2: Define general interfaces between the NBDRA components
Stage 3: Validate the NBDRA by building Big Data general applications through the general interfaces

Potential areas of future work for the Subgroup during stage 2 are highlighted in Section 1.5 of this volume. The current effort documented in this volume reflects concepts developed within the rapidly evolving field of Big Data.

1 INTRODUCTION

1.1 BACKGROUND

There is broad agreement among commercial, academic, and government leaders about the remarkable potential of Big Data to spark innovation, fuel commerce, and drive progress. Big Data is the common term used to describe the deluge of data in today's networked, digitized, sensor-laden, and information-driven world. The availability of vast data resources carries the potential to answer questions previously out of reach, including the following:

- How can a potential pandemic reliably be detected early enough to intervene?
- Can new materials with advanced properties be predicted before these materials have ever been synthesized?
- How can the current advantage of the attacker over the defender in guarding against cyber-security threats be reversed?

There is also broad agreement on the ability of Big Data to overwhelm traditional approaches. The growth rates for data volumes, speeds, and complexity are outpacing scientific and technological advances in data analytics, management, transport, and data user spheres.

Despite widespread agreement on the inherent opportunities and current limitations of Big Data, a lack of consensus on some important, fundamental questions continues to confuse potential users and stymie progress. These questions include the following:

- What attributes define Big Data solutions?
- How is Big Data different from traditional data environments and related applications?
- What are the essential characteristics of Big Data environments?
- How do these environments integrate with currently deployed architectures?
- What are the central scientific, technological, and standardization challenges that need to be addressed to accelerate the deployment of robust Big Data solutions?

Within this context, on March 29, 2012, the White House announced the Big Data Research and Development Initiative.[1] The initiative's goals include helping to accelerate the pace of discovery in science and engineering, strengthening national security, and transforming teaching and learning by improving the ability to extract knowledge and insights from large and complex collections of digital data.

Six federal departments and their agencies announced more than $200 million in commitments spread across more than 80 projects, which aim to significantly improve the tools and techniques needed to access, organize, and draw conclusions from huge volumes of digital data. The initiative also challenged industry, research universities, and nonprofits to join with the federal government to make the most of the opportunities created by Big Data.

Motivated by the White House initiative and public suggestions, the National Institute of Standards and Technology (NIST) has accepted the challenge to stimulate collaboration among industry professionals to further the secure and effective adoption of Big Data. As one result of NIST's Cloud and Big Data Forum held on January 15–17, 2013, there was strong encouragement for NIST to create a public working group for the development of a Big Data Interoperability Framework. Forum participants noted that this roadmap should define and prioritize Big Data requirements, including interoperability, portability, reusability, extensibility, data usage, analytics, and technology infrastructure. In doing so, the roadmap would accelerate the adoption of the most secure and effective Big Data techniques and technology.

On June 19, 2013, the NIST Big Data Public Working Group (NBD-PWG) was launched with extensive participation by industry, academia, and government from across the nation. The scope of the NBD-PWG involves forming a community of interests from all sectors—including industry, academia, and government—with the goal of developing consensus on definitions, taxonomies, secure reference architectures, security and privacy, and—from these—a standards roadmap. Such a consensus would create a vendor-neutral, technology- and infrastructure-independent framework that would enable Big Data stakeholders to identify and use the best analytics tools for their processing and visualization requirements on the most suitable computing platform and cluster, while also allowing value-added from Big Data service providers.

The *NIST Big Data Interoperability Framework* consists of seven volumes, each of which addresses a specific key topic, resulting from the work of the NBD-PWG. The seven volumes are as follows:

- Volume 1, Definitions
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The *NIST Big Data Interoperability Framework* will be released in three versions, which correspond to the three stages of the NBD-PWG work. The three stages aim to achieve the following with respect to the NBDRA:

Stage 1: Identify the high-level Big Data reference architecture key components, which are technology, infrastructure, and vendor agnostic
Stage 2: Define general interfaces between the NBDRA components
Stage 3: Validate the NBDRA by building Big Data general applications through the general interfaces

Potential areas of future work for the Subgroup during stage 2 are highlighted in Section 1.5 of this volume. The current effort documented in this volume reflects concepts developed within the rapidly evolving field of Big Data.

1.2 SCOPE AND OBJECTIVES OF THE REFERENCE ARCHITECTURES SUBGROUP

Reference architectures provide "an authoritative source of information about a specific subject area that guides and constrains the instantiations of multiple architectures and solutions." [2] Reference architectures generally serve as a foundation for solution architectures and may also be used for comparison and alignment of instantiations of architectures and solutions.

The goal of the NBD-PWG Reference Architecture Subgroup is to develop an open reference architecture for Big Data that achieves the following objectives:

- Provides a common language for the various stakeholders
- Encourages adherence to common standards, specifications, and patterns
- Provides consistent methods for implementation of technology to solve similar problem sets
- Illustrates and improves understanding of the various Big Data components, processes, and systems, in the context of a vendor- and technology- agnostic Big Data conceptual model
- Provides a technical reference for U.S. government departments, agencies, and other consumers to understand, discuss, categorize, and compare Big Data solutions
- Facilitates analysis of candidate standards for interoperability, portability, reusability, and extendibility

The NIST Big Data Reference Architecture (NBDRA) is a high-level conceptual model crafted to serve as a tool to facilitate open discussion of the requirements, design structures, and operations inherent in Big Data. The NBDRA is intended to facilitate the understanding of the operational intricacies in Big Data. It does not represent the system architecture of a specific Big Data system, but rather is a tool for describing, discussing, and developing system-specific architectures using a common framework of reference. The model is not tied to any specific vendor products, services, or reference implementation, nor does it define prescriptive solutions that inhibit innovation.

The NBDRA does not address the following:

- Detailed specifications for any organization's operational systems
- Detailed specifications of information exchanges or services
- Recommendations or standards for integration of infrastructure products

1.3 REPORT PRODUCTION

A wide spectrum of Big Data architectures have been explored and developed as part of various industry, academic, and government initiatives. The development of the NBDRA and material contained in this volume involved the following steps:

1. Announce that the NBD-PWG Reference Architecture Subgroup is open to the public to attract and solicit a wide array of subject matter experts and stakeholders in government, industry, and academia
2. Gather publicly-available Big Data architectures and materials representing various stakeholders, different data types, and diverse use cases [a]
3. Examine and analyze the Big Data material to better understand existing concepts, usage, goals, objectives, characteristics, and key elements of Big Data, and then document the findings using NIST's Big Data taxonomies model (presented in *NIST Big Data Interoperability Framework: Volume 2, Taxonomies*)
4. Develop a technology-independent, open reference architecture based on the analysis of Big Data material and inputs received from other NBD-PWG subgroups

1.4 REPORT STRUCTURE

The organization of this document roughly corresponds to the process used by the NBD-PWG to develop the NBDRA. Following the introductory material presented in Section 1, the remainder of this document is organized as follows:

- Section 2 contains high-level, system requirements in support of Big Data relevant to the design of the NBDRA and discusses the development of these requirements
- Section 3 presents the generic, technology-independent NBDRA conceptual model
- Section 4 discusses the five main functional components of the NBDRA
- Section 5 describes the system and lifecycle management considerations related to the NBDRA management fabric
- Section 6 briefly introduces security and privacy topics related to the security and privacy fabric of the NBDRA
- Appendix A summarizes deployment considerations
- Appendix B lists the terms and definitions in this document
- Appendix C provides examples of Big Data logical data architecture options

[a] Many of the architecture use cases were originally collected by the NBD-PWG Use Case and Requirements Subgroup and can be accessed at http://bigdatawg.nist.gov/usecases.php.

- Appendix D defines the acronyms used in this document
- Appendix E lists several general resources that provide additional information on topics covered in this document and specific references in this document

1.5 FUTURE WORK ON THIS VOLUME

The *NIST Big Data Interoperability Framework* will be released in three versions, which correspond to the three stages of the NBD-PWG work. The three stages aim to achieve the following with respect to the NBDRA:

Stage 1: Identify the common reference architecture components of Big Data implementations and formulate the technology-independent NBDRA
Stage 2: Define general interfaces between the NBDRA components
Stage 3: Validate the NBDRA by building Big Data general applications through the general interfaces

This document (Version 1) presents the overall NBDRA components and fabrics with high-level description and functionalities.

Version 2 activities will focus on the definition of general interfaces between the NBDRA components by performing the following:

- Select use cases from the 62 (51 general and 11 security and privacy) submitted use cases or other, to be identified, meaningful use cases
- Work with domain experts to identify workflow and interactions among the NBDRA components and fabrics
- Explore and model these interactions within a small scale, manageable, and well-defined confined environment
- Aggregate the common data workflow and interactions between NBDRA components and fabrics and package them into general interfaces

Version 3 activities will focus on validation of the NBDRA through the use of the defined NBDRA general interfaces to build general Big Data applications. The validation strategy will include the following:

- Implement the same set of use cases used in Version 2 by using the defined general interfaces
- Identify and implement a few new use cases outside the Version 2 scenarios
- Enhance general NBDRA interfaces through lessons learned from the implementations in Version 3 activities

The general interfaces developed during Version 2 activities will offer a starting point for further refinement by any interested parties and is not intended to be a definitive solution to address all implementation needs.

2 HIGH LEVEL REFERENCE ARCHITECTURE REQUIREMENTS

The development of a Big Data reference architecture requires a thorough understanding of current techniques, issues, and concerns. To this end, the NBD-PWG collected use cases to gain an understanding of current applications of Big Data, conducted a survey of reference architectures to understand commonalities within Big Data architectures in use, developed a taxonomy to understand and organize the information collected, and reviewed existing technologies and trends relevant to Big Data. The results of these NBD-PWG activities were used in the development of the NBDRA and are briefly described in this section.

2.1 USE CASES AND REQUIREMENTS

To develop the use cases, publically available information was collected for various Big Data architectures in nine broad areas, or application domains. Participants in the NBD-PWG Use Case and Requirements Subgroup and other interested parties provided the use case details via a template, which helped standardize the responses and facilitate subsequent analysis and comparison of the use cases. However, submissions still varied in levels of detail, quantitative data, or qualitative information. The *NIST Big Data Interoperability Framework: Volume 3, Use Cases and General Requirements* document presents the original use cases, an analysis of the compiled information, and the requirements extracted from the use cases.

The extracted requirements represent challenges faced in seven characterization categories (Table 1) developed by the Subgroup. Requirements specific to the use cases were aggregated into high level, generalized requirements, which are vendor and technology neutral.

The use case characterization categories were used as input in the development of the NBDRA and map directly to NBDRA components and fabrics as shown in Table 1.

Table 1: Mapping Use Case Characterization Categories to Reference Architecture Components and Fabrics

USE CASE CHARACTERIZATION CATEGORIES		REFERENCE ARCHITECTURE COMPONENTS AND FABRICS
Data sources	→	Data Provider
Data transformation	→	Big Data Application Provider
Capabilities	→	Big Data Framework Provider
Data consumer	→	Data Consumer
Security and privacy	→	Security and Privacy Fabric
Lifecycle management	→	System Orchestrator; Management Fabric
Other requirements	→	To all components and fabrics

The high-level, generalized requirements are presented below. The development of these generalized requirements is presented in the *NIST Big Data Interoperability Framework: Volume 3, Use Cases and Requirements* document.

DATA PROVIDER REQUIREMENTS

- DSR-1: Reliable, real-time, asynchronous, streaming, and batch processing to collect data from centralized, distributed, and cloud data sources, sensors, or instruments
- DSR-2: Slow, bursty, and high throughput data transmission between data sources and computing clusters
- DSR-3: Diversified data content ranging from structured and unstructured text, documents, graphs, web sites, geospatial, compressed, timed, spatial, multimedia, simulation, and instrumental (i.e., system managements and monitoring) data

BIG DATA APPLICATION PROVIDER REQUIREMENTS

- TPR-1: Diversified, compute-intensive, analytic processing and machine learning techniques
- TPR-2: Batch and real time analytic processing
- TPR-3: Processing large diversified data content and modeling
- TPR-4: Processing data in motion (e.g., streaming, fetching new content, data tracking, traceability, data change management, and data boundaries)

BIG DATA FRAMEWORK PROVIDER REQUIREMENTS

- CPR-1: Legacy software and advanced software packages
- CPR-2: Legacy and advanced computing platforms
- CPR-3: Legacy and advanced distributed computing clusters, co-processors, input/output (I/O) processing
- CPR-4: Advanced networks (e.g., Software Defined Networks [SDN]) and elastic data transmission, including fiber, cable, and wireless networks (e.g., local area network [LAN], wide area network [WAN], metropolitan area network [MAN], Wi-Fi)
- CPR-5: Legacy, large, virtual, and advanced distributed data storage
- CPR-6: Legacy and advanced programming executables, applications, tools, utilities, and libraries

DATA CONSUMER REQUIREMENTS

- DCR-1: Fast searches (~0.1 seconds) from processed data with high relevancy, accuracy, and recall
- DCR-2: Diversified output file formats for visualization, rendering, and reporting
- DCR-3: Visual layout for results presentation
- DCR-4: Rich user interface for access using browser, visualization tools
- DCR-5: High resolution, multi-dimension layer of data visualization
- DCR-6: Streaming results to clients

SECURITY AND PRIVACY REQUIREMENTS

- SPR-1: Protect and preserve security and privacy of sensitive data
- SPR-2: Support sandbox, access control, and multi-tenant, multi-level, policy-driven authentication on protected data and ensure these are in line with accepted governance, risk, and compliance (GRC) and confidentiality, integrity, and availability (CIA) best practices

MANAGEMENT REQUIREMENTS

- LMR-1: Data quality curation, including pre-processing, data clustering, classification, reduction, and format transformation
- LMR-2: Dynamic updates on data, user profiles, and links
- LMR-3: Data lifecycle and long-term preservation policy, including data provenance
- LMR-4: Data validation

- LMR-5: Human annotation for data validation
- LMR-6: Prevention of data loss or corruption
- LMR-7: Multi-site (including cross-border, geographically dispersed) archives
- LMR-8: Persistent identifier and data traceability
- LMR-9: Standardization, aggregation, and normalization of data from disparate sources

OTHER REQUIREMENTS

- OR-1: Rich user interface from mobile platforms to access processed results
- OR-2: Performance monitoring on analytic processing from mobile platforms
- OR-3: Rich visual content search and rendering from mobile platforms
- OR-4: Mobile device data acquisition and management
- OR-5: Security across mobile devices and other smart devices such as sensors

2.2 REFERENCE ARCHITECTURE SURVEY

The NBD-PWG Reference Architecture Subgroup conducted a survey of current reference architectures to advance the understanding of the operational intricacies in Big Data and to serve as a tool for developing system-specific architectures using a common reference framework. The Subgroup surveyed currently published Big Data platforms by leading companies or individuals supporting the Big Data framework and analyzed the collected material. This effort revealed a consistency between Big Data architectures that served in the development of the NBDRA. Survey details, methodology, and conclusions are reported in *NIST Big Data Interoperability Framework: Volume 5, Architectures White Paper Survey*.

2.3 TAXONOMY

The NBD-PWG Definitions and Taxonomy Subgroup focused on identifying Big Data concepts, defining terms needed to describe the new Big Data paradigm, and defining reference architecture terms. The reference architecture taxonomy presented below provides a hierarchy of the components of the reference architecture. Additional taxonomy details are presented in the *NIST Big Data Interoperability Framework: Volume 2, Taxonomy* document.

Figure 1 outlines potential actors for the seven roles developed by the NBD-PWG Definition and Taxonomy Subgroup. The blue boxes contain the name of the role at the top with potential actors listed directly below.

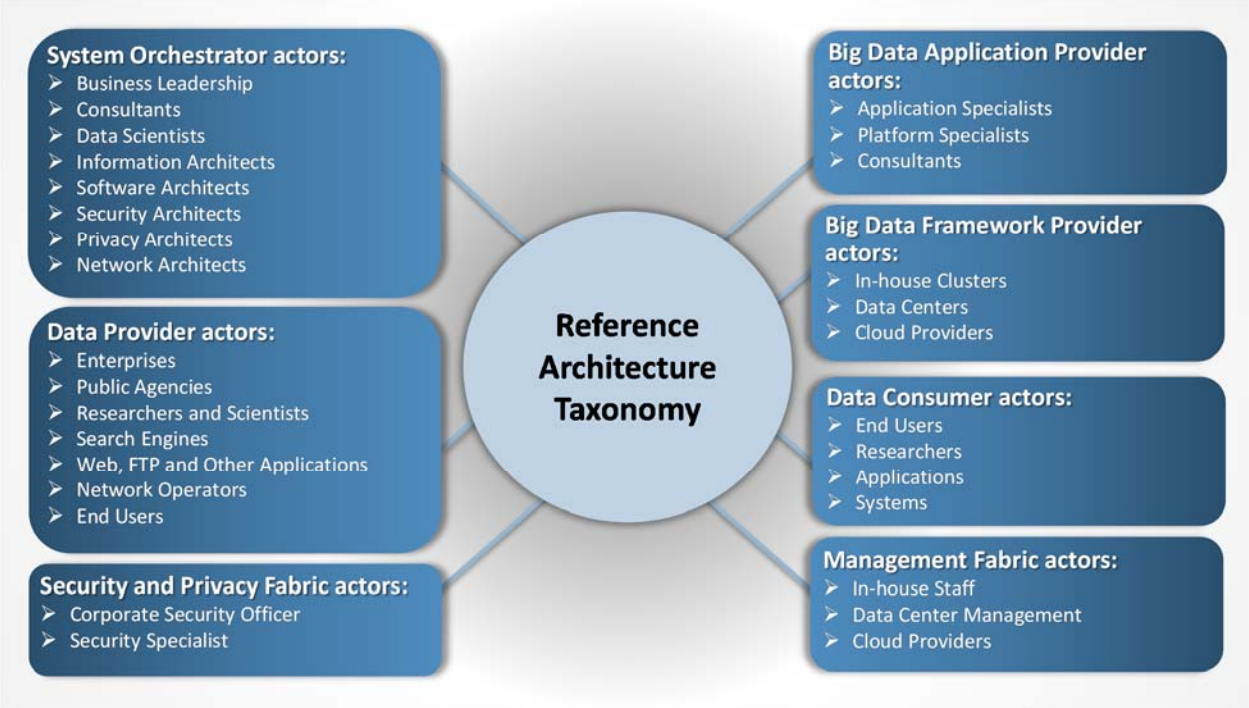


Figure 1: NBDRA Taxonomy

SYSTEM ORCHESTRATOR

The System Orchestrator provides the overarching requirements that the system must fulfill, including policy, governance, architecture, resources, and business requirements, as well as monitoring or auditing activities to ensure the system complies with those requirements. The System Orchestrator role provides system requirements, high-level design, and monitoring for the data system. While the role pre-dates Big Data systems, some related design activities have changed within the Big Data paradigm.

DATA PROVIDER

A Data Provider makes data available to itself or to others. In fulfilling its role, the Data Provider creates an abstraction of various types of data sources (such as raw data or data previously transformed by another system) and makes them available through different functional interfaces. The actor fulfilling this role can be part of the Big Data system, internal to the organization in another system, or external to the organization orchestrating the system. While the concept of a Data Provider is not new, the greater data collection and analytics capabilities have opened up new possibilities for providing valuable data.

BIG DATA APPLICATION PROVIDER

The Big Data Application Provider executes the manipulations of the data lifecycle to meet requirements established by the System Orchestrator. This is where the general capabilities within the Big Data framework are combined to produce the specific data system. While the activities of an application provider are the same whether the solution being built concerns Big Data or not, the methods and techniques have changed because the data and data processing is parallelized across resources.

BIG DATA FRAMEWORK PROVIDER

The Big Data Framework Provider has general resources or services to be used by the Big Data Application Provider in the creation of the specific application. There are many new components from which the Big Data Application Provider can choose in using these resources and the network to build the specific system. This is the role that has seen the most significant changes because of Big Data. The Big Data Framework Provider consists of one or more instances of the three subcomponents: infrastructure

frameworks, data platforms, and processing frameworks. There is no requirement that all instances at a given level in the hierarchy be of the same technology and, in fact, most Big Data implementations are hybrids combining multiple technology approaches. These provide flexibility and can meet the complete range of requirements that are driven from the Big Data Application Provider. Due to the rapid emergence of new techniques, this is an area that will continue to need discussion.

DATA CONSUMER

The Data Consumer receives the value output of the Big Data system. In many respects, it is the recipient of the same type of functional interfaces that the Data Provider exposes to the Big Data Application Provider. After the system adds value to the original data sources, the Big Data Application Provider then exposes that same type of functional interfaces to the Data Consumer.

SECURITY AND PRIVACY FABRIC

Security and privacy issues affect all other components of the NBDRA. The Security and Privacy Fabric interacts with the System Orchestrator for policy, requirements, and auditing and also with both the Big Data Application Provider and the Big Data Framework Provider for development, deployment, and operation. The *NIST Big Data Interoperability Framework: Volume 4, Security and Privacy* document discusses security and privacy topics.

MANAGEMENT FABRIC

The Big Data characteristics of volume, velocity, variety, and variability demand a versatile system and software management platform for provisioning, software and package configuration and management, along with resource and performance monitoring and management. Big Data management involves system, data, security, and privacy considerations at scale, while maintaining a high level of data quality and secure accessibility.

3 NBDRA CONCEPTUAL MODEL

As discussed in Section 2, the NBD-PWG Reference Architecture Subgroup used a variety of inputs from other NBD-PWG subgroups in developing a vendor-neutral, technology- and infrastructure-agnostic, conceptual model of Big Data architecture. This conceptual model, the NBDRA, is shown in Figure 2 and represents a Big Data system comprised of five logical functional components connected by interoperability interfaces (i.e., services). Two fabrics envelop the components, representing the interwoven nature of management and security and privacy with all five of the components.

The NBDRA is intended to enable system engineers, data scientists, software developers, data architects, and senior decision makers to develop solutions to issues that require diverse approaches due to convergence of Big Data characteristics within an interoperable Big Data ecosystem. It provides a framework to support a variety of business environments, including tightly-integrated enterprise systems and loosely-coupled vertical industries, by enhancing understanding of how Big Data complements and differs from existing analytics, business intelligence, databases, and systems.

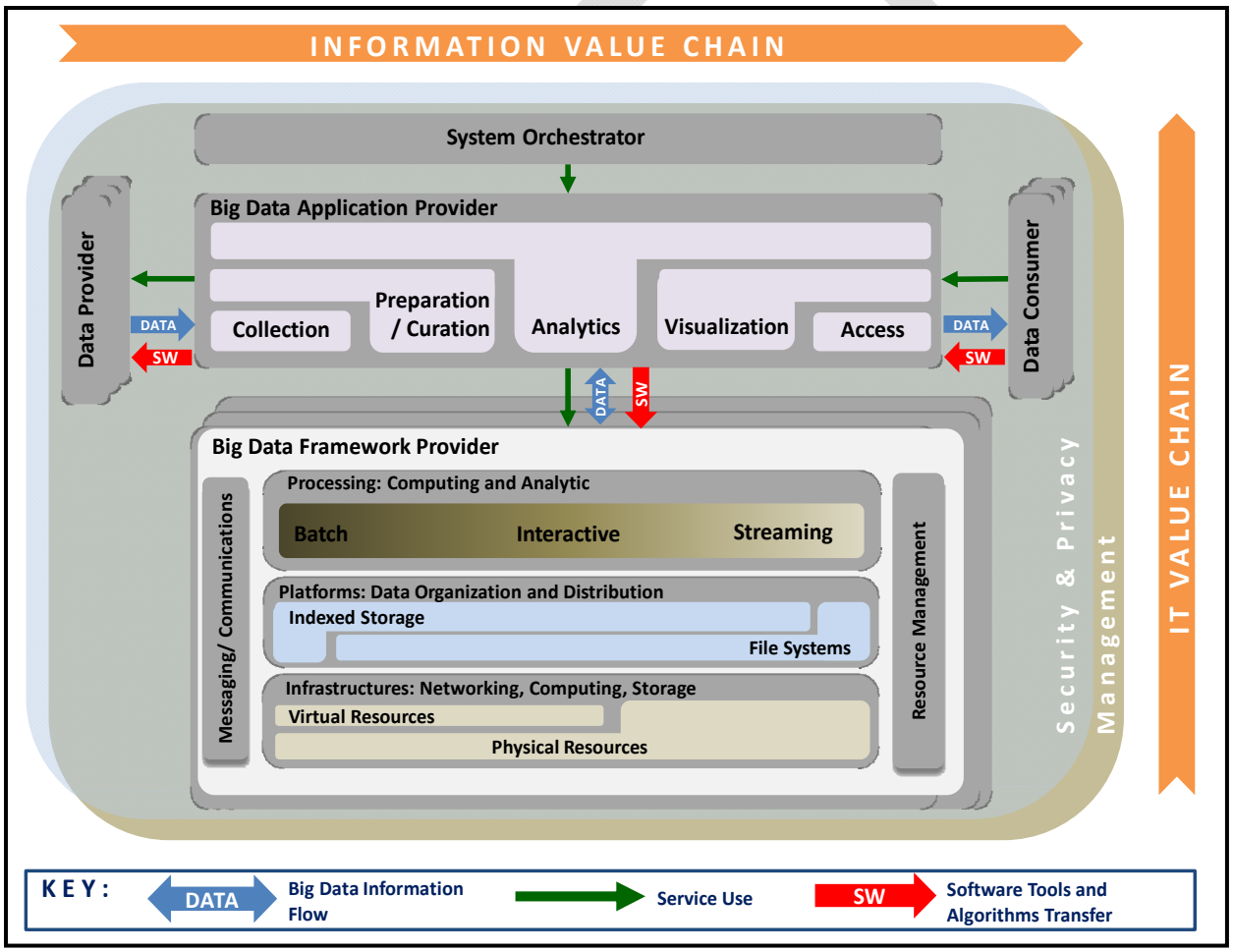


Figure 2: NIST Big Data Reference Architecture (NBDRA)

The NBDRA is organized around two axes representing the two Big Data value chains: the information (horizontal axis) and the IT (vertical axis). Along the information axis, the value is created by data

collection, integration, analysis, and applying the results following the value chain. Along the IT axis, the value is created by providing networking, infrastructure, platforms, application tools, and other IT services for hosting of and operating the Big Data in support of required data applications. At the intersection of both axes is the Big Data Application Provider component, indicating that data analytics and its implementation provide the value to Big Data stakeholders in both value chains. The names of the Big Data Application Provider and Big Data Framework Provider components contain "providers" to indicate that these components provide or implement a specific technical function within the system.

The five main NBDRA components, shown in Figure 2 and discussed in detail in Section 4, represent different technical roles that exist in every Big Data system. These functional components are as follows:

- System Orchestrator
- Data Provider
- Big Data Application Provider
- Big Data Framework Provider
- Data Consumer

The two fabrics shown in Figure 2 encompassing the five functional components are the following:

- Management
- Security and Privacy

These two fabrics provide services and functionality to the five functional components in the areas specific to Big Data and are crucial to any Big Data solution.

The "DATA" arrows in Figure 2 show the flow of data between the system's main components. Data flows between the components either physically (i.e., by value) or by providing its location and the means to access it (i.e., by reference). The "SW" arrows show transfer of software tools for processing of Big Data *in situ*. The "Service Use" arrows represent software programmable interfaces. While the main focus of the NBDRA is to represent the run-time environment, all three types of communications or transactions can happen in the configuration phase as well. Manual agreements (e.g., service-level agreements [SLAs]) and human interactions that may exist throughout the system are not shown in the NBDRA.

The components represent functional roles in the Big Data ecosystem. In system development, actors and roles have the same relationship as in the movies, but system development actors can represent individuals, organizations, software, or hardware. According to the Big Data taxonomy, a single actor can play multiple roles, and multiple actors can play the same role. The NBDRA does not specify the business boundaries between the participating actors or stakeholders, so the roles can either reside within the same business entity or can be implemented by different business entities. Therefore, the NBDRA is applicable to a variety of business environments, from tightly-integrated enterprise systems to loosely-coupled vertical industries that rely on the cooperation of independent stakeholders. As a result, the notion of internal versus external functional components or roles does not apply to the NBDRA. However, for a specific use case, once the roles are associated with specific business stakeholders, the functional components would be considered as internal or external—subject to the use case's point of view.

The NBDRA does support the representation of stacking or chaining of Big Data systems. For example, a Data Consumer of one system could serve as a Data Provider to the next system down the stack or chain.

4 FUNCTIONAL COMPONENTS OF THE NBDRA

As outlined in Section 3, the five main functional components of the NBDRA represent the different technical roles within a Big Data system. The functional components are listed below and discussed in subsequent subsections.

- **System Orchestrator**: Defines and integrates the required data application activities into an operational vertical system
- **Data Provider**: Introduces new data or information feeds into the Big Data system
- **Big Data Application Provider**: Executes a data lifecycle to meet security and privacy requirements as well as System Orchestrator-defined requirements
- **Big Data Framework Provider**: Establishes a computing framework in which to execute certain transformation applications while protecting the privacy and integrity of data
- **Data Consumer**: Includes end users or other systems that use the results of the Big Data Application Provider

4.1 SYSTEM ORCHESTRATOR

The System Orchestrator role includes defining and integrating the required data application activities into an operational vertical system. Typically, the System Orchestrator involves a collection of more specific roles, performed by one or more actors, which manage and orchestrate the operation of the Big Data system. These actors may be human components, software components, or some combination of the two. The function of the System Orchestrator is to configure and manage the other components of the Big Data architecture to implement one or more workloads that the architecture is designed to execute. The workloads managed by the System Orchestrator may be assigning/provisioning framework components to individual physical or virtual nodes at the lower level, or providing a graphical user interface that supports the specification of workflows linking together multiple applications and components at the higher level. The System Orchestrator may also, through the Management Fabric, monitor the workloads and system to confirm that specific quality of service requirements are met for each workload, and may actually elastically assign and provision additional physical or virtual resources to meet workload requirements resulting from changes/surges in the data or number of users/transactions.

The NBDRA represents a broad range of Big Data systems, from tightly coupled enterprise solutions (integrated by standard or proprietary interfaces) to loosely coupled vertical systems maintained by a variety of stakeholders bounded by agreements and standard or standard-de-facto interfaces.

In an enterprise environment, the System Orchestrator role is typically centralized and can be mapped to the traditional role of system governor that provides the overarching requirements and constraints, which the system must fulfill, including policy, architecture, resources, or business requirements. A system governor works with a collection of other roles (e.g., data manager, data security, and system manager) to implement the requirements and the system's functionality.

In a loosely coupled vertical system, the System Orchestrator role is typically decentralized. Each independent stakeholder is responsible for its own system management, security, and integration, as well as integration within the Big Data distributed system using the interfaces provided by other stakeholders.

4.2 DATA PROVIDER

The Data Provider role introduces new data or information feeds into the Big Data system for discovery, access, and transformation by the Big Data system. New data feeds are distinct from the data already in use by the system and residing in the various system repositories. Similar technologies can be used to

446 access both new data feeds and existing data. The Data Provider actors can be anything from a sensor, to
447 a human inputting data manually, to another Big Data system.

448 One of the important characteristics of a Big Data system is the ability to import and use data from a
449 variety of data sources. Data sources can be internal or public records, tapes, images, audio, videos,
450 sensor data, web logs, system and audit logs, HTTP cookies, and other sources. Humans, machines,
451 sensors, online and offline applications, Internet technologies, and other actors can also produce data
452 sources. The roles of Data Provider and Big Data Application Provider often belong to different
453 organizations, unless the organization implementing the Big Data Application Provider owns the data
454 sources. Consequently, data from different sources may have different security and privacy
455 considerations. In fulfilling its role, the Data Provider creates an abstraction of the data sources. In the
456 case of raw data sources, the Data Provider can potentially cleanse, correct, and store the data in an
457 internal format that is accessible to the Big Data system that will ingest it.

458 The Data Provider can also provide an abstraction of data previously transformed by another system (i.e.,
459 legacy system, another Big Data system.) In this case, the Data Provider would represent a Data
460 Consumer of the other system. For example, Data Provider 1 could generate a streaming data source from
461 the operations performed by Data Provider 2 on a dataset at rest.

462 Data Provider activities include the following, which are common to most systems that handle data:

463 • Collecting the data
464 • Persisting the data
465 • Providing transformation functions for data scrubbing of sensitive information such as
466 Personally Identifiable Information (PII)
467 • Creating the metadata describing the data source(s), usage policies/access rights, and other
468 relevant attributes
469 • Enforcing access rights on data access
470 • Establishing formal or informal contracts for data access authorizations
471 • Making the data accessible through suitable programmable push or pull interfaces
472 • Providing push or pull access mechanisms
473 • Publishing the availability of the information and the means to access it

474 The Data Provider exposes a collection of interfaces (or services) for discovering and accessing the data.
475 These interfaces would typically include a registry so that applications can locate a Data Provider,
476 identify the data of interest it contains, understand the types of access allowed, understand the types of
477 analysis supported, locate the data source, determine data access methods, identify the data security
478 requirements, identify the data privacy requirements, and other pertinent information. Therefore, the
479 interface would provide the means to register the data source, query the registry, and identify a standard
480 set of data contained by the registry.

481 Subject to Big Data characteristics (i.e., volume, variety, velocity, and variability) and system design
482 considerations, interfaces for exposing and accessing data would vary in their complexity and can include
483 both push and pull software mechanisms. These mechanisms can include subscription to events, listening
484 to data feeds, querying for specific data properties or content, and the ability to submit a code for
485 execution to process the data *in situ.* Because the data can be too large to economically move across the
486 network, the interface could also allow the submission of analysis requests (e.g., software code
487 implementing a certain algorithm for execution), with the results returned to the requestor. Data access
488 may not always be automated, but might involve a human role logging into the system and providing
489 directions where new data should be transferred (e.g., establishing a subscription to an email based data
490 feed).

491 The interface between the Data Provider and Big Data Application Provider typically will go through
492 three phases: initiation, data transfer, and termination. The initiation phase is started by either party and

often includes some level of authentication/authorization. The phase may also include queries for metadata about the source or consumer, such as the list of available topics in a publish/subscribe (pub/sub) model and the transfer of any parameters (e.g., object count/size limits or target storage locations). Alternatively, the phase may be as simple as one side opening a socket connection to a known port on the other side.

The data transfer phase may be a push from the Data Provider or a pull by the Big Data Application Provider. It may also be a singular transfer or involve multiple repeating transfers. In a repeating transfer situation, the data may be a continuous stream of transactions/records/bytes. In a push scenario, the Big Data Application Provider must be prepared to accept the data asynchronously but may also be required to acknowledge (or negatively acknowledge) the receipt of each unit of data. In a pull scenario, the Big Data Application Provider would specifically generate a request that defines through parameters of the data to be returned. The returned data could itself be a stream or multiple records/units of data and the data transfer phase may consist of multiple request/send transactions.

The termination phase could be as simple as one side simply dropping the connection or could include checksums, counts, hashes, or other information about the completed transfer.

4.3 BIG DATA APPLICATION PROVIDER

The Big Data Application Provider role executes a specific set of operations along the data lifecycle to meet the requirements established by the System Orchestrator, as well as meeting security and privacy requirements. The Big Data Application Provider is the architecture component that encapsulates the business logic and functionality to be executed by the architecture. The Big Data Application Provider activities include the following

- Collection
- Preparation
- Analytics
- Visualization
- Access

These activities are represented by the subcomponents of the Big Data Application Provider as shown in Figure 2. The execution of these activities would typically be specific to the application and, therefore, are not candidates for standardization. However, the metadata and the policies defined and exchanged between the application's subcomponents could be standardized when the application is specific to a vertical industry.

While many of these activities exist in traditional data processing systems, the data volume, velocity, variety, and variability present in Big Data systems radically change their implementation. Traditional algorithms and mechanisms of traditional data processing implementations need to be adjusted and optimized to create applications that are responsive and can grow to handle ever growing data collections.

As data propagates through the ecosystem, it is being processed and transformed in different ways in order to extract the value from the information. Each activity of the Big Data Application Provider can be implemented by independent stakeholders and deployed as stand-alone services.

The Big Data Application Provider can be a single instance or a collection of more granular Big Data Application Providers, each implementing different steps in the data lifecycle. Each of the activities of the Big Data Application Provider may be a general service invoked by the System Orchestrator, Data Provider, or Data Consumer, such as a Web server, a file server, a collection of one or more application programs, or a combination. There may be multiple and differing instances of each activity or a single program may perform multiple activities. Each of the activities is able to interact with the underlying Big Data Framework Providers as well as with the Data Providers and Data Consumers. In addition, these

activities may execute in parallel or in any number of sequences and will frequently communicate with each other through the messaging/communications element of the Big Data Framework Provider. Also, the functions of the Big Data Application Provider, specifically the collection and access activities, will interact with the Security and Privacy Fabric to perform authentication/authorization and record/maintain data provenance.

Each of the functions can run on a separate Big Data Framework Provider or all can use a common Big Data Framework Provider. The considerations behind these different system approaches would depend on potentially different technological needs, business and/or deployment constraints (including privacy), and other policy considerations. The baseline NBDRA does not show the underlying technologies, business considerations, and topological constraints, thus making it applicable to any kind of system approach and deployment.

For example, the infrastructure of the Big Data Application Provider would be represented as one of the Big Data Framework Providers. If the Big Data Application Provider uses external/outsourced infrastructures as well, it or they will be represented as another or multiple Big Data Framework Providers in the NBDRA. The multiple grey blocks behind the Big Data Framework Providers in Figure 2 indicate that multiple Big Data Framework Providers can support a single Big Data Application Provider.

4.3.1 COLLECTION

In general, the collection activity of the Big Data Application Provider handles the interface with the Data Provider. This may be a general service, such as a file server or web server configured by the System Orchestrator to accept or perform specific collections of data, or it may be an application specific service designed to pull data or receive pushes of data from the Data Provider. Since this activity is receiving data at a minimum, it must store/buffer the received data until it is persisted through the Big Data Framework Provider. This persistence need not be to physical media but may simply be to an in-memory queue or other service provided by the processing frameworks of the Big Data Framework Provider. The collection activity is likely where the extraction portion of the Extract, Transform, Load/Extract, Load, Transform (ETL/ELT) cycle is performed. At the initial collection stage, sets of data (e.g., data records) of similar structure are collected (and combined), resulting in uniform security, policy, and other considerations. Initial metadata is created (e.g., subjects with keys are identified) to facilitate subsequent aggregation or lookup methods.

4.3.2 PREPARATION

The preparation activity is where the transformation portion of the ETL/ELT cycle is likely performed, although analytics activity will also likely perform advanced parts of the transformation. Tasks performed by this activity could include data validation (e.g., checksums/hashes, format checks), cleansing (e.g., eliminating bad records/fields), outlier removal, standardization, reformatting, or encapsulating. This activity is also where source data will frequently be persisted to archive storage in the Big Data Framework Provider and provenance data will be verified or attached/associated. Verification or attachment may include optimization of data through manipulations (e.g., deduplication) and indexing to optimize the analytics process. This activity may also aggregate data from different Data Providers, leveraging metadata keys to create an expanded and enhanced data set.

4.3.3 ANALYTICS

The analytics activity of the Big Data Application Provider includes the encoding of the low-level business logic of the Big Data system (with higher level business process logic being encoded by the System Orchestrator). The activity implements the techniques to extract knowledge from the data based on the requirements of the vertical application. The requirements specify the data processing algorithms for processing the data to produce new insights that will address the technical goal. The analytics activity will leverage the processing frameworks to implement the associated logic. This typically involves the activity providing software that implements the analytic logic to the batch and/or streaming elements of

the processing framework for execution. The messaging/communication framework of the Big Data Framework Provider may be used to pass data or control functions to the application logic running in the processing frameworks. The analytic logic may be broken up into multiple modules to be executed by the processing frameworks which communicate, through the messaging/communication framework, with each other and other functions instantiated by the Big Data Application Provider.

4.3.4 VISUALIZATION

The visualization activity of the Big Data Application Provider prepares elements of the processed data and the output of the analytic activity for presentation to the Data Consumer. The objective of this activity is to format and present data in such a way as to optimally communicate meaning and knowledge. The visualization preparation may involve producing a text-based report or rendering the analytic results as some form of graphic. The resulting output may be a static visualization and may simply be stored through the Big Data Framework Provider for later access. However, the visualization activity frequently interacts with the access activity, the analytics activity, and the Big Data Framework Provider (processing and platform) to provide interactive visualization of the data to the Data Consumer based on parameters provided to the access activity by the Data Consumer. The visualization activity may be completely application implemented, leverage one or more application libraries, or may use specialized visualization processing frameworks within the Big Data Framework Provider.

4.3.5 ACCESS

The access activity within the Big Data Application Provider is focused on the communication/interaction with the Data Consumer. Similar to the collection activity, the access activity may be a generic service such as a web server or application server that is configured by the System Orchestrator to handle specific requests from the Data Consumer. This activity would interface with the visualization and analytic activities to respond to requests from the Data Consumer (who may be a person) and uses the processing and platform frameworks to retrieve data to respond to Data Consumer requests. In addition, the access activity confirms that descriptive and administrative metadata and metadata schemes are captured and maintained for access by the Data Consumer and as data is transferred to the Data Consumer. The interface with the Data Consumer may be synchronous or asynchronous in nature and may use a pull or push paradigm for data transfer.

4.4 BIG DATA FRAMEWORK PROVIDER

The Big Data Framework Provider typically consists of one or more hierarchically organized instances of the components in the NBDRA IT value chain (Figure 2). There is no requirement that all instances at a given level in the hierarchy be of the same technology. In fact, most Big Data implementations are hybrids that combine multiple technology approaches in order to provide flexibility or meet the complete range of requirements, which are driven from the Big Data Application Provider.

Many of the recent advances related to Big Data have been in the area of frameworks designed to scale to Big Data needs (e.g., addressing volume, variety, velocity, and variability) while maintaining linear or near linear performance. These advances have generated much of the technology excitement in the Big Data space. Accordingly, there is a great deal more information available in the frameworks area compared to the other components and the additional detail provided for the Big Data Framework Provider in this document reflects this imbalance.

The Big Data Framework Provider is comprised of the following three subcomponents (from the bottom to the top):

- Infrastructure Frameworks
- Data Platform Frameworks
- Processing Frameworks

4.4.1 INFRASTRUCTURE FRAMEWORKS

This Big Data Framework Provider element provides all of the resources necessary to host/run the activities of the other components of the Big Data system. Typically, these resources consist of some combination of physical resources, which may host/support similar virtual resources. These resources are generally classified as follows:

- Networking: These are the resources that transfer data from one infrastructure framework component to another
- Computing: These are the physical processors and memory that execute and hold the software of the other Big Data system components
- Storage: These are resources which provide persistence of the data in a Big Data system
- Environmental: These are the physical plant resources (power, cooling) that must be accounted for when establishing an instance of a Big Data system

While the Big Data Framework Provider component may be deployed directly on physical resources or on virtual resources, at some level all resources have a physical representation. Physical resources are frequently used to deploy multiple components that will be duplicated across a large number of physical nodes to provide what is known as horizontal scalability. Virtualization is frequently used to achieve elasticity and flexibility in the allocation of physical resources and is often referred to as Infrastructure as a Service (IaaS) within the cloud computing community. Virtualization is typically found in one of three basic forms within a Big Data Architecture.

- Native: In this form, a hypervisor runs natively on the bare metal and manages multiple virtual machines consisting of Operating Systems (OS) and applications.
- Hosted: In this form, an OS runs natively on the bare metal and a hypervisor runs on top of that to host a client OS and applications. This model is not often seen in Big Data architectures due to the increased overhead of the extra OS layer.
- Containerized: In this form, hypervisor functions are embedded in the OS, which runs on bare metal. Applications are run inside containers, which control or limit access to the OS and physical machine resources. This approach has gained popularity for Big Data architectures because it further reduces overhead since most OS functions are a single shared resource. It may not be considered as secure or stable since in the event that the container controls/limits fail, one application may take down every application sharing those physical resources.

The following subsections describe the types of physical and virtual resources that comprise Big Data infrastructure.

4.4.1.1 NETWORKING

The connectivity of the architecture infrastructure should be addressed, as it affects the velocity characteristic of Big Data. While, some Big Data implementations may solely deal with data that is already resident in the data center and does not need to leave the confines of the local network, others may need to plan and account for the movement of Big Data either into or out of the data center. The location of Big Data systems with transfer requirements may depend on the availability of external network connectivity (i.e., bandwidth) and the limitations of Transmission Control Protocol (TCP) where there is low latency (as measured by packet Round Trip Time) with the primary senders or receivers of Big Data. To address the limitations of TCP, architects for Big Data systems may need to consider some of the advanced non-TCP based communications protocols available that are specifically designed to transfer large files such as video and imagery.

Overall availability of the external links is another infrastructure aspect relating to the velocity characteristic of Big Data that should be considered in architecting external connectivity. A given connectivity link may be able to easily handle the velocity of data while operating correctly. However, should the quality of service on the link degrade or the link fail completely, data may be lost or simply

back up to the point that it can never recover. Use cases exist where the contingency planning for network outages involves transferring data to physical media and physically transporting it to the desired destination. However, even this approach is limited by the time it may require to transfer the data to external media for transport.

The volume and velocity characteristics of Big Data often are driving factors in the implementation of the internal network infrastructure as well. For example, if the implementation requires frequent transfers of large multi-gigabyte files between cluster nodes, then high speed and low latency links are required. Depending on the availability requirements, redundant and fault tolerant links may be required. Other aspects of the network infrastructure include name resolution (e.g., Domain Name Server [DNS]) and encryption along with firewalls and other perimeter access control capabilities. Finally, the network infrastructure may also include automated deployment, provisioning capabilities, or agents and infrastructure wide monitoring agents that are leveraged by the management/communication elements to implement a specific model.

Two concepts, Software Defined Networks (SDN) and Network Function Virtualization (NFV), have recently been developed in support of scalable networks and scalable systems using them.

4.4.1.1.1 Software Defined Networks

Frequently ignored, but critical to the performance of distributed systems and frameworks, and especially critical to Big Data implementations, is the efficient and effective management of networking resources. Significant advances in network resource management have been realized through what is known as SDN. Much like virtualization frameworks manage shared pools of CPU/memory/disk, SDNs (or virtual networks) manage pools of physical network resources. In contrast to the traditional approaches of dedicated physical network links for data, management, I/O, and control, SDNs contain multiple physical resources (including links and actual switching fabric) that are pooled and allocated as required to specific functions and sometimes to specific applications. This allocation can consist of raw bandwidth, quality of service (QOS) priority, and even actual data routes.

4.4.1.1.2 Network Function Virtualization

With the advent of virtualization, virtual appliances can now reasonably support a large number of network functions that were traditionally performed by dedicated devices. Network functions that can be implemented in this manner include routing/routers, perimeter defense (e.g., firewalls), remote access authorization, and network traffic/load monitoring. Some key advantages of NFV include elasticity, fault tolerance, and resource management. For example, the ability to automatically deploy/provision additional firewalls in response to a surge in user or data connections and then un-deploy them when the surge is over can be critical in handling the volumes associated with Big Data.

4.4.1.2 COMPUTING

The logical distribution of cluster/computing infrastructure may vary from a dense grid of physical commodity machines in a rack, to a set of virtual machines running on a cloud service provider, or to a loosely coupled set of machines distributed around the globe providing access to un-used computing resources. Computing infrastructure also frequently includes the underlying operating systems and associated services used to interconnect the cluster resources via the networking elements.

4.4.1.3 STORAGE

The storage infrastructure may include any resource from isolated local disks to Storage Area Networks (SANs) or network attached storage.

Two aspects of storage infrastructure technology that directly influence their suitability for Big Data solutions are capacity and transfer bandwidth. Capacity refers to the ability to handle the data volume. Local disks/file systems are specifically limited by the size of the available media. Hardware or software (HW/SW) redundant array of independent disks (RAID) solutions—in this case local to a processing

node—help with scaling by allowing multiple pieces of media to be treated as a single device. However, this approach is limited by the physical dimension of the media and the number of devices the node can accept. SAN and network-attached storage (NAS) implementations—often known as shared disk solutions—remove that limit by consolidating storage into a storage specific device. By consolidating storage, the second aspect—transfer bandwidth—may become an issue. While both network and I/O interfaces are getting faster and many implementations support multiple transfer channels, I/O bandwidth can still be a limiting factor. In addition, despite the redundancies provided by RAID, hot spares, multiple power supplies, and multiple controllers, these boxes can often become I/O bottlenecks or single points of failure in an enterprise. Many Big Data implementations address these issues by using distributed file systems within the platform framework.

4.4.1.4 ENVIRONMENTAL RESOURCES

Environmental resources, such as power and heating, ventilation, and air conditioning (HVAC), are critical to the Big Data Framework Provider. While environmental resources are critical to the operation of the Big Data system, they are not within the technical boundaries and are, therefore, not depicted in Figure 2, the NBDRA conceptual model.

Adequately sized infrastructure to support application requirements is critical to the success of Big Data implementations. The infrastructure architecture operational requirements range from basic power and cooling to external bandwidth connectivity (as discussed above). A key evolution that has been driven by Big Data is the increase in server density (i.e., more CPU/memory/disk per rack unit). However, with this increased density, infrastructure—specifically power and cooling—may not be distributed within the data center to allow for sufficient power to each rack or adequate air flow to remove excess heat. In addition, with the high cost of managing energy consumption within data centers, technologies have been developed that actually power down or idle resources not in use to save energy or to reduce consumption during peak periods.

4.4.2 DATA PLATFORM FRAMEWORKS

Data Platform Frameworks provide for the logical data organization and distribution combined with the associated access application programming interfaces (APIs) or methods. The frameworks may also include data registry and metadata services along with semantic data descriptions such as formal ontologies or taxonomies. The logical data organization may range from simple delimited flat files to fully distributed relational or columnar data stores. The storage mediums range from high latency robotic tape drives, to spinning magnetic media, to flash/solid state disks, or to random access memory. Accordingly, the access methods may range from file access APIs to query languages such as SQL. Typical Big Data framework implementations would support either basic file system style storage or in-memory storage and one or more indexed storage approaches. Based on the specific Big Data system considerations, this logical organization may or may not be distributed across a cluster of computing resources.

In most aspects, the logical data organization and distribution in Big Data storage frameworks mirrors the common approach for most legacy systems. Figure 3 presents a brief overview of data organization approaches for Big Data.

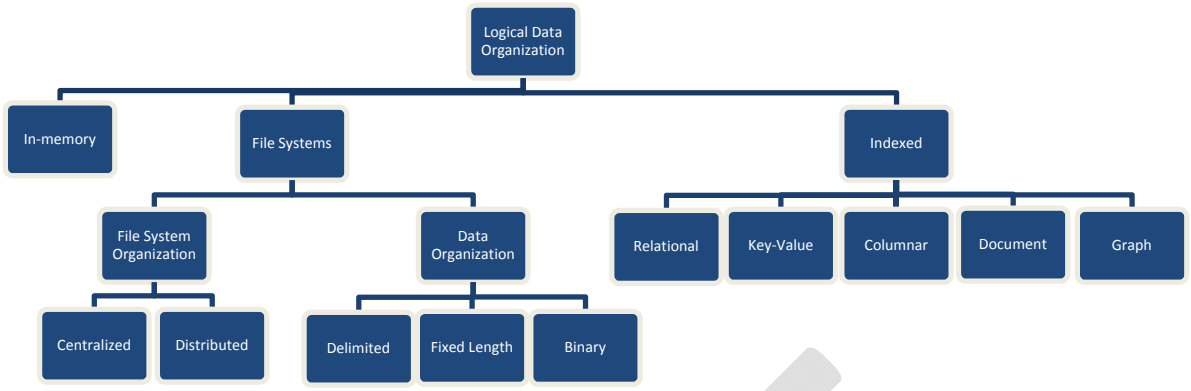


Figure 3: Data Organization Approaches

Many Big Data logical storage organizations leverage the common file system concept—where chunks of data are organized into a hierarchical namespace of directories—as their base and then implement various indexing methods within the individual files. This allows many of these approaches to be run both on simple local storage file systems for testing purposes or on fully distributed file systems for scale.

4.4.2.1 IN-MEMORY

The infrastructure illustrated in the NBDRA (Figure 2) indicates that physical resources are required to support analytics. However, such infrastructure will vary (i.e., will be optimized) for the Big Data characteristics of the problem under study. Large, but static, historical datasets with no urgent analysis time constraints would optimize the infrastructure for the volume characteristic of Big Data, while time-critical analyses such as intrusion detection or social media trend analysis would optimize the infrastructure for the velocity characteristic of Big Data. Velocity implies the necessity for extremely fast analysis and the infrastructure to support it—namely, very low latency, in-memory analytics.

In-memory database technologies are increasingly used due to the significant reduction in memory prices and the increased scalability of modern servers and operating systems. Yet, an in-memory element of a velocity-oriented infrastructure will require more than simply massive random-access memory (RAM). It will also require optimized data structures and memory access algorithms to fully exploit RAM performance. Current in-memory database offerings are beginning to address this issue.

Traditional database management architectures are designed to use spinning disks as the primary storage mechanism, with the main memory of the computing environment relegated to providing caching of data and indexes. Many of these in-memory storage mechanisms have their roots in the massively parallel processing and super computer environments popular in the scientific community.

These approaches should not be confused with solid state (e.g., flash) disks or tiered storage systems that implement memory-based storage which simply replicate the disk style interfaces and data structures but with faster storage medium. Actual in-memory storage systems typically eschew the overhead of file system semantics and optimize the data storage structure to minimize memory footprint and maximize the data access rates. These in-memory systems may implement general purpose relational and other NoSQL style organization and interfaces or be completely optimized to a specific problem and data structure.

Like traditional disk-based systems for Big Data, these implementations frequently support horizontal distribution of data and processing across multiple independent nodes—although shared memory technologies are still prevalent in specialized implementations. Unlike traditional disk-based approaches, in-memory solutions and the supported applications must account for the lack of persistence of the data across system failures. Some implementations leverage a hybrid approach involving write-through to more persistent storage to help alleviate the issue.

The advantages of in-memory approaches include faster processing of intensive analysis and reporting workloads. In-memory systems are especially good for analysis of real time data such as that needed for some complex event processing of streams. For reporting workloads, performance improvements can often be on the order of several hundred times faster—especially for sparse matrix and simulation type analytics.

4.4.2.2 FILE SYSTEMS

Many Big Data processing frameworks and applications access their data directly from underlying file systems. In almost all cases, the file systems implement some level of the Portable Operating System Interface (POSIX) standards for permissions and the associated file operations. This allows other higher-level frameworks for indexing or processing to operate with relative transparency as to whether the underlying file system is local or fully distributed. File-based approaches consist of two layers, the file system organization and the data organization within the files.

4.4.2.2.1 File System Organization

File systems tend to be either centralized or distributed. Centralized file systems are basically implementations of local file systems that are placed on a single large storage platform (e.g., SAN or NAS) and accessed via some network capability. In a virtual environment, multiple physical centralized file systems may be combined, split, or allocated to create multiple logical file systems.

Distributed file systems (also known as cluster file systems) seek to overcome the throughput issues presented by the volume and velocity characteristics of big data combine I/O throughput across multiple devices (spindles) on each node, with redundancy and failover mirroring or replicating data at the block level across multiple nodes. The data replication is specifically designed to allow the use of heterogeneous commodity hardware across the Big Data cluster. Thus, if a single drive or an entire node should fail, no data is lost because it is replicated on other nodes and throughput is only minimally affected because that processing can be moved to the other nodes. In addition, replication allows for high levels of concurrency for reading data and for initial writes. Updates and transaction style changes tend to be an issue for many distributed file systems because latency in creating replicated blocks will create consistency issues (e.g., a block is changed but another node reads the old data before it is replicated.) Several file system implementations also support data compression and encryption at various levels. One major caveat is that, for distributed block based file systems, the compression/encryption must be splittable and allow any given block to be decompressed/ decrypted out of sequence and without access to the other blocks.

Distributed object stores (DOSs) (also known as global object stores) are a unique example of distributed file system organization. Unlike the approaches described above, which implement a traditional file system hierarchy namespace approach, DOSs present a flat name space with a globally unique identifier (GUID) for any given chunk of data. Generally, data in the store is located through a query against a metadata catalog that returns the associated GUIDs. The GUID generally provides the underlying software implementation with the storage location of the data of interest. These object stores are developed and marketed for storage of very large data objects, from complete data sets to large individual objects (e.g., high resolution images in the tens of gigabytes [GBs] size range). The biggest limitation of these stores for Big Data tends to be network throughput (i.e., speed) because many require the object to be accessed in total. However, future trends point to the concept of being able to send the computation/application to the data versus needing to bring the data to the application.

From a maturity perspective, two key areas where distributed file systems are likely to improve are (1) random write I/O performance and consistency, and (2) the generation of de facto standards at a similar or greater level as the Internet Engineering Task Force (IETF) Requests for Comments (RFC), such as those currently available for the network file system (NFS) protocol. DOSs, while currently available and operational from several commercial providers and part of the roadmap for large organizations such as the National Geospatial Intelligence Agency (NGA), currently are essentially proprietary implementations.

For DOSs to become prevalent within Big Data ecosystems, there should be: some level of interoperability available (i.e., through standardized APIs); standards-based approaches for data discovery; and, most importantly, standards-based approaches that allow the application to be transferred over the grid and run locally to the data versus transferring the data to the application.

4.4.2.2.2 In File Data Organization

Very little is different in Big Data for in file data organization. File based data can be text, binary data, fixed length records, or some sort of delimited structure (e.g., comma separated values [CSV], Extensible Markup Language [XML]). For record oriented storage (either delimited or fixed length), this generally is not an issue for Big Data unless individual records can exceed a block size. Some distributed file system implementations provide compression at the volume or directory level and implement it below the logical block level (e.g., when a block is read from the file system, it is decompressed/decrypted before being returned).Because of their simplicity, familiarity, and portability, delimited files are frequently the default storage format in many Big Data implementations. The tradeoff is I/O efficiency (i.e., speed). While individual blocks in a distributed file system might be accessed in parallel, each block still needs to be read in sequence. In the case of a delimited file, if only the last field of certain records is of interest with perhaps hundreds of fields, a lot of I/O and processing bandwidth is wasted.

Binary formats tend to be application or implementation specific. While they can offer much more efficient access due to smaller data sizes (i.e., integers are two to four bytes in binary while they are one byte per digit in ASCII [American Standard Code for Information Interchange]), they offer limited portability between different implementations. At least one popular distributed file system provides its own standard binary format, which allows data to be portable between multiple applications without additional software. However, the bulk of the indexed data organization approaches discussed below leverage binary formats for efficiency.

4.4.2.3 INDEXED STORAGE ORGANIZATION

The very nature of Big Data (primarily the volume and velocity characteristics) practically drives requirements to some form of indexing structure. Big Data volume requires that specific data elements be located quickly without scanning across the entire dataset. Big Data velocity also requires that data can be located quickly either for matching (e.g., incoming data matches something in an existing data set) or to know where to write/update new data.

The choice of a particular indexing method or methods depends mostly on the data and the nature of the application to be implemented. For example, graph data (i.e., vertices, edges, and properties) can easily be represented in flat text files as vertex-edge pairs, edge-vertex-vertex triples, or vertex-edge list records. However, processing this data efficiently would require potentially loading the entire data set into memory or being able to distribute the application and data set across multiple nodes so a portion of the graph is in memory on each node. Splitting the graph across nodes requires the nodes to communicate when graph sections have vertices that connect with vertices on other processing nodes. This is perfectly acceptable for some graph applications—such as shortest path—especially when the graph is static. Some graph processing frameworks operate using this exact model. However, this approach is infeasible for large scale graphs requiring a specialized graph storage framework, where the graph is dynamic or searching or matching to a portion of the graph is needed quickly.

Indexing approaches tend to be classified by the features provided in the implementation, specifically: the complexity of the data structures that can be stored; how well they can process links between data; and, how easily they support multiple access patterns as shown in Figure 4. Since any of these features can be implemented in custom application code, the values portrayed represent approximate norms. For example, key-value (KV) stores work well for data that is only accessed through a single key, whose values can be expressed in a single flat structure, and where multiple records do not need to be related. While document stores can support very complex structures of arbitrary width and tend to be indexed for access via multiple document properties, they do not tend to support inter-record relationships well.

It is noted that the specific implementations for each storage approach vary significantly enough that all of the values for the features represented here are really ranges. For example, relational data storage implementations are supporting increasingly complex data structures and on going work aims to add more flexible access patterns natively in BigTable columnar implementations. Within Big Data, the performance of each of these features tends to drive the scalability of that approach depending on the problem being solved. For example, if the problem is to locate a single piece of data for a unique key, then KV stores will scale really well. However, if a problem requires general navigation of the relationships between multiple data records, a graph storage model will likely provide the best performance.

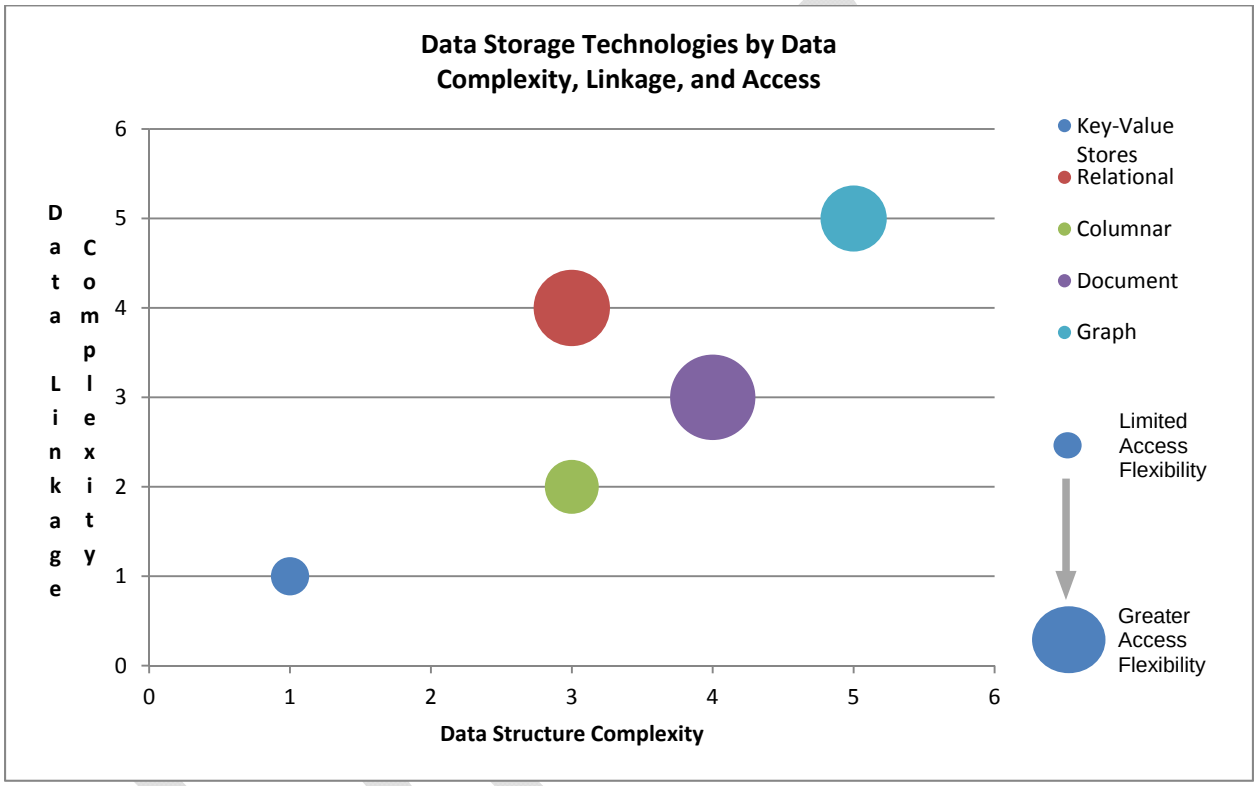


Figure 4: Data Storage Technologies

4.4.3 PROCESSING FRAMEWORKS

The processing frameworks for Big Data provide the necessary infrastructure software to support implementation of applications that can deal with the volume, velocity, variety, and variability of data. Processing frameworks define how the computation and processing of the data is organized. Big Data applications rely on various platforms and technologies to meet the challenges of scalable data analytics and operation.

Processing frameworks generally focus on data manipulation, which falls along a continuum between batch and streaming oriented processing. However, depending on the specific data organization platform, and actual processing requested, any given framework may support a range of data manipulation from high latency to NRT processing. Overall, many Big Data architectures will include multiple frameworks to support a wide range of requirements.

Typically, processing frameworks are categorized based on whether they support batch or streaming processing. This categorization is generally stated from the user perspective (e.g., how fast does a user get a response to a request). However, Big Data processing frameworks actually have three processing phases: data ingestion, data analysis, and data dissemination, which closely follow the flow of data through the architecture. The Big Data Application Provider activities control the application of specific framework capabilities to these processing phases. The batch-streaming continuum, illustrated in the processing subcomponent in Figure 2, can be applied to the three distinct processing phases. For example, data may enter a Big Data system at high velocity and the end user must quickly retrieve a summary of the prior day's data. In this case, the ingestion of the data into the system needs to be near real time (NRT) and keep up with the data stream. The analysis portion could be incremental (e.g., performed as the data is ingested) or could be a batch process performed at a specified time, while retrieval (i.e., read visualization) of the data could be interactive. Specific to the use case, data transformation may take place at any point during its transit through the system. For example, the ingestion phase may only write the data as quickly as possible, or it may run some foundational analysis to track incrementally computed information such as minimum, maximum, average. The core processing job may only perform the analytic elements required by the Big Data Application Provider and compute a matrix of data or may actually generate some rendering like a heat map to support the visualization component. To permit rapid display, the data dissemination phase almost certainly does some rendering, but the extent depends on the nature of the data and the visualization.

For the purposes of this discussion, most processing frameworks can be described with respect to their primary location within the information flow illustrated in Figure 5.

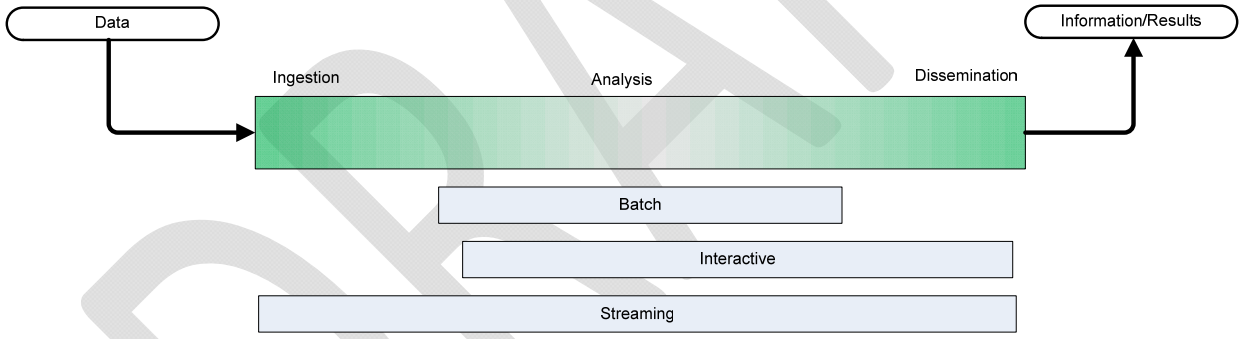


Figure 5: Information Flow

The green shading in Figure 5 illustrates the general sensitivity of that processing phase to latency, which is defined as the time from when a request or piece of data arrives at a system until its processing/delivery is complete. For Big Data, the ingestion may or may not require NRT performance to keep up with the data flow. Some types of analytics (specifically those categorized as complex event processing [CEP]) may or may not require NRT processing. The Data Consumer generally is located at the far right of Figure 5, depending upon the use case and application batch responses (e.g., a nightly report is emailed) may be sufficient. In other cases, the user may be willing to wait minutes for the results of a query to be returned, or they may need immediate alerting when critical information arrives at the system. In general, batch analytics tend to better support long term strategic decision making, where the overall view or direction is not affected by the latest small changes in the underlying data. Streaming analytics are better suited for tactical decision making, where new data needs to be acted upon immediately. A primary use case for streaming analytics would be electronic trading on stock exchanges where the window to act on a given piece of data can be measured in microseconds. Messaging and communication provides the transfer of data between processing elements and the buffering necessary to deal with the deltas in data rate, processing times, and data requests.

Typically, Big Data discussions focus around the categories of batch and streaming frameworks for analytics. However, frameworks for retrieval of data that provide interactive access to Big Data are becoming a more prevalent. It is noted that the lines between these categories are not solid or distinct, with some frameworks providing aspects of each category.

4.4.3.1 BATCH FRAMEWORKS

Batch frameworks, whose roots stem from the mainframe processing era, are some of the most prevalent and mature components of a Big Data architecture because the historically long processing times for large data volumes. Batch frameworks ideally are not tied to a particular algorithm or even algorithm type, but rather provide a programming model where multiple classes of algorithms can be implemented. Also, when discussed in terms of Big Data, these processing models are frequently distributed across multiple nodes of a cluster. They are routinely differentiated by the amount of data sharing between processes/activities within the model.

In 2004, a list of algorithms for simulation in the physical sciences was developed that became known as the "Seven Dwarfs".[3] The list was recently modified and extended to the 13 algorithms (Table 2), based on the following definition: "A dwarf is an algorithmic method that computes a pattern of computation and communication."[4]

Table 2: 13 Dwarfs—Algorithms for Simulation in the Physical Sciences

Dense Linear Algebra*	Combinational Logic
Sparse Linear Algebra*	Graph Traversal
Spectral methods	Dynamic Programming
N-Body Methods	Backtrack and Branch-and-Bound
Structured Grids*	Graphical Models
Unstructured Grids*	Finite State Machines
Map/Reduce	

Notes:
* Indicates one of the original seven dwarfs. The recent list modification removed three of the original seven algorithms: Fast Fourier Transform, Particles, and Monte Carlo.

Many other algorithms or processing models have been defined over the years two of the best-known models in the Big Data space, Map/Reduce (M/R) and Bulk Synchronous Parallel (BSP), are described in the following subsections.

4.4.3.1.1 Map/Reduce

Several major Internet search providers popularized the M/R model as they worked to implement their search capabilities. In general, M/R programs follow five basic stages:

1. Input preparation and assignment to mappers
2. Map a set of keys and values to new keys and values: Map(k1,v1) → list(k2,v2)
3. Shuffle data to each reducer and each reducer sorts its input—each reducer is assigned a set of keys (k2)
4. Run the reduce on a list(v2) associated with each key and produce an output: Reduce(k2, list(v2)) → list(v3)
5. Final output the lists(v3) from each reducer are combined and sorted by k2

While there is a single output, nothing in the model prohibits multiple input data sets. It is extremely common for complex analytics to be built as workflows of multiple M/R jobs. While the M/R programming model is best suited to aggregation (e.g., sum, average, group-by) type analytics, a wide variety of analytic algorithms have been implemented within processing frameworks. M/R does not

generally perform well with applications or algorithms that need to directly update the underlying data. For example, updating the values for a single key would require the entire data set be read, output, and then moved or copied over the original data set. Because the mappers and reducers are stateless in nature, applications that require iterative computation on parts of the data or repeated access to parts of the data set do not tend to scale or perform well under M/R.

Due to its shared nothing approach, the usability of M/R for Big Data applications has made it popular enough that a number of large data storage solutions (mostly those of the NoSQL variety) provide implementations within their architecture. One major criticism of M/R early on was that the interfaces to most implementations were at too low of a level (written in Java or JavaScript.) However many of the more prevalent implementations now support high level procedural and declarative language interfaces and even visual programming environments are beginning to appear.

4.4.3.1.2 Bulk Synchronous Parallel

The BSP programming model, originally developed by Leslie Valiant[5], combines parallel processing with the ability of processing modules to send messages to other processing modules and explicit synchronization of the steps. A BSP algorithm is composed of what are termed "supersteps", which are comprised of the following three distinct elements.

- Bulk Parallel Computation: Each processor performs the calculation/analysis on its local chunk of data.
- Message Passing: As each processor performs its calculations it may generate messages to other processors. These messages are frequently updates to values associated with the local data of other processors but may also result in the creation of additional data.
- Synchronization: Once a processor has completed processing its local data it pauses until all other processors have also completed their processing.

This cycle can be terminated by all the processors "voting to stop", which will generally happen when a processor has generated no messages to other processors (e.g., no updates). All processors voting to stop in turn indicates that there are no new updates to any processors' data and the computation is complete. Alternatively, the cycle may be terminated after a fixed number of supersteps have been completed (e.g., after a certain number of iterations of a Monte Carlo simulation).

The advantage of BSP over Map/Reduce is that processing can actually create updates to the data being processed. It is this distinction that has made BSP popular for graph processing and simulations where computations on one node/element of data directly affect values or connections with other nodes/elements. The disadvantage of BSP is the high cost of the synchronization barrier between supersteps. Should the distribution of data or processing between processors become highly unbalanced then some processors may become overloaded while others remain idle.

Numerous extensions and enhancements to the basic BSP model have been developed and implemented over the years, many of which are designed to address the balancing and cost of synchronization problems.

4.4.3.2 STREAMING FRAMEWORKS

Streaming frameworks are built to deal with data that requires processing as fast or faster than the velocity at which it arrives into the Big Data system. The primary goal of streaming frameworks is to reduce the latency between the arrival of data into the system and the creation, storage, or presentation of the results. Complex Event Processing (CEP) is one of the problem domains frequently addressed by streaming frameworks. CEP uses data from one or more streams/sources to infer or identify events or patterns in NRT.

Almost all streaming frameworks for Big Data available today implement some form of basic workflow processing for the streams. These workflows use messaging/communications frameworks to pass data

objects (often referred to as events) between steps in the workflow. This frequently takes the form of a directed execution graph. The distinguishing characteristics of streaming frameworks are typically organized around the following three characteristics: event ordering and processing guarantees, state management, and partitioning/parallelism. These three characteristics are described below.

4.4.3.2.1 Event Ordering and Processing Guarantees

This characteristic refers to whether stream processing elements are guaranteed to see messages or events in the order they are received by the Big Data System, as well as how often a message or event may or may not be processed. In a non-distributed and single stream mode, this type of guarantee is relatively trivial. Once distributed and/or multiple streams are added to the system, the guarantee becomes more complicated. With distributed processing, the guarantees must be enforced for each partition of the data (partitioning and parallelism as further described below.) Complications arise when the process/task/job dealing with a partition dies. Processing guarantees are typically divided into the following three classes:

- At-most-once delivery: This is the simplest form of guarantee and allows for messages or events to be dropped if there is a failure in processing or communications or if they arrive out of order. This class of guarantee is applicable for data where there is no dependence of new events on the state of the data created by prior events.
- At-least-once delivery: Within this class, the frameworks will track each message or event (and any downstream messages or events generated) to verify that it is processed within a configured time frame. Messages or events that are not processed in the time allowed are re-introduced into the stream. This mode requires extensive state management by the framework (and sometimes the associated application) to track which events have been processed by which stages of the workflow. However, under this class, messages or events may be processed more than once and also may arrive out of order. This class of guarantee is appropriate for systems where every message or event must be processed regardless of the order (e.g., no dependence on prior events), and the application either is not affected by duplicate processing of events or has the ability to de-duplicate events itself.
- Exactly-once delivery: This class of framework processing requires the same top level state tracking as At-least-once delivery but embeds mechanisms within the framework to detect and ignore duplicates. This class often guarantees ordering of event arrivals and is required for applications where the processing of any given event is dependent on the processing of prior events. It is noted that these guarantees only apply to data handling within the framework. If data is passed outside the framework processing topology, then by an application then the application must ensure the processing state is maintained by the topology or duplicate data may be forwarded to non-framework elements of the application.

In the latter two classes, some form of unique key must be associated with each message or event to support de-duplication and event ordering. Often, this key will contain some form of timestamp plus the stream ID to uniquely identify each message in the stream.

4.4.3.2.2 State Management

A critical characteristic of stream processing frameworks is their ability to recover and not lose critical data in the event of a process or node failure within the framework. Frameworks typically provide this state management through persistence of the data to some form of storage. This persistence can be: local, allowing the failed process to be restarted on the same node; a remote or distributed data store, allowing the process to be restarted on any node; or, local storage that is replicated to other nodes. The tradeoff between these storage methods is the latency introduced by the persistence. Both the amount of state data persisted and the time required to assure that the data is persisted contribute to the latency. In the case of a remote or distributed data store, the latency required is generally dependent on the extent to which the data store implements ACID (Atomicity, Consistency, Isolation, Durability) or BASE (Basically Available, Soft state, Eventual consistency)style consistency. With replication of local storage, the

reliability of the state management is entirely tied to the ability of the replication to recover in the event of a process or node failure. Sometimes this state replication is actually implemented using the same messaging/communication framework that is used to communicate with and between stream processors. Some frameworks actually support full transaction semantics, including multi-stage commits and transaction rollbacks. The tradeoff is the same one that exists for any transaction system is that any type of ACID-like guarantee will introduce latency. Too much latency at any point in the stream flow can create bottlenecks and, depending on the ordering or processing guarantees, can result in deadlock or loop states—especially when some level of failure is present.

4.4.3.2.3 Partitioning and Parallelism

This streaming framework characteristic relates to the distribution of data across nodes and worker tasks to provide the horizontal scalability needed to address the volume and velocity of Big Data streams. This partitioning scheme must interact with the resource management framework to allocate resources. The even distribution of data across partitions is essential so that the associated work is evenly distributed. The even data distribution directly relates to selection of a key (e.g., user ID, host name) that can be evenly distributed. The simplest form might be using a number that increments by one and then is processed with a modulus function of the number of tasks/workers available. If data dependencies require all records with a common key be processed by the same worker, then assuring an even data distribution over the life of the stream can be difficult. Some streaming frameworks address this issue by supporting dynamic partitioning where the partition of overloaded workers is split and allocated to existing workers or newly created workers. To achieve success—especially with a data/state dependency related to the key—it is critical that the framework have state management, which allows the associated state data to be moved/transitioned to the new/different worker.

4.4.4 MESSAGING/COMMUNICATIONS FRAMEWORKS

Messaging and communications frameworks have their roots in the High Performance Computing (HPC) environments long popular in the scientific and research communities. Messaging/Communications Frameworks were developed to provide APIs for the reliable queuing, transmission, and receipt of data between nodes in a horizontally scaled cluster. These frameworks typically implement either a point-to-point transfer model or a store-and-forward model in their architecture. Under a point-to-point model, data is transferred directly from the sender to the receivers. The majority of point-to-point implementations do not provide for any form of message recovery should there be a program crash or interruption in the communications link between sender and receiver. These frameworks typically implement all logic within the sender and receiver program space, including any delivery guarantees or message retransmission capabilities. One common variation of this model is the implementation of multicast (i.e., one-to-many or many-to-many distribution), which allows the sender to broadcast the messages over a "channel", and receivers in turn listen to those channels of interest. Typically, multicast messaging does not implement any form of guaranteed receipt. With the store-and-forward model, the sender would address the message to one or more receivers and send it to an intermediate broker, which would store the message and then forward it on to the receivers. Many of these implementations support some form of persistence for messages not yet delivered, providing for recovery in the event of process or system failure. Multicast messaging can also be implemented in this model and is frequently referred to as a pub/sub model.

4.4.5 RESOURCE MANAGEMENT FRAMEWORK

As Big Data systems have evolved and become more complex, and as businesses work to leverage limited computation and storage resources to address a broader range of applications and business challenges, the requirement to effectively manage those resources has grown significantly. While tools for resource management and "elastic computing" have expanded and matured in response to the needs of cloud providers and virtualization technologies, Big Data introduces unique requirements for these tools.

1134 However, Big Data frameworks tend to fall more into a distributed computing paradigm, which presents
1135 additional challenges.

1136 The Big Data characteristics of volume and velocity drive the requirements with respect to Big Data
1137 resource management. Elastic computing (i.e., spawning another instance of some service) is the most
1138 common approach to address expansion in volume or velocity of data entering the system. CPU and
1139 memory are the two resources that tend to be most essential to managing Big Data situations. While
1140 shortages or over-allocation of either will have significant impacts on system performance, improper or
1141 inefficient memory management is frequently catastrophic. Big Data differs and becomes more complex
1142 in the allocation of computing resources to different storage or processing frameworks that are optimized
1143 for specific applications and data structures. As such, resource management frameworks will often use
1144 data locality as one of the input variables in determining where new processing framework elements (e.g.,
1145 master nodes, processing nodes, job slots) are instantiated. Importantly, because the data is big (i.e., large
1146 volume), it generally is not feasible to move data to the processing frameworks. In addition, while nearly
1147 all Big Data processing frameworks can be run in virtualized environments, most are designed to run on
1148 bare metal commodity hardware to provide efficient I/O for the volume of the data.

1149 Two distinct approaches to resource management in Big Data frameworks are evolving. The first is intra-
1150 framework resource management, where the framework itself manages allocation of resources between its
1151 various components. This allocation is typically driven by the framework's workload and often seeks to
1152 "turn off" unneeded resources to either minimize overall demands of the framework on the system or to
1153 minimize the operating cost of the system by reducing energy use. With this approach, applications can
1154 seek to schedule and request resources that—much like main frame operating systems of the past—are
1155 managed through scheduling queues and job classes.

1156 The second approach is inter-framework resource management, which is designed to address the needs of
1157 many Big Data systems to support multiple storage and processing frameworks that can address and be
1158 optimized for a wide range of applications. With this approach, the resource management framework
1159 actually runs as a service that supports and manages resource requests from frameworks, monitoring
1160 framework resource usage, and in some cases manages application queues. In many ways, this approach
1161 is like the resource management layers common in cloud/virtualization environments, and there are
1162 efforts underway to create hybrid resource management frameworks that handle both physical and virtual
1163 resources.

1164 Taking these concepts further and combining them is resulting in the emerging technologies built around
1165 what is being termed software-defined data centers (SDDCs). This expansion on elastic and cloud
1166 computing goes beyond the management of fixed pools of physical resources as virtual resources to
1167 include the automated deployment and provisioning of features and capabilities onto physical resources.
1168 For example, automated deployment tools that interface with virtualization or other framework APIs can
1169 be used to automatically stand up entire clusters or to add additional physical resources to physical or
1170 virtual clusters.

1171 4.5 DATA CONSUMER

1172 Similar to the Data Provider, the role of Data Consumer within the NBDRA can be an actual end user or
1173 another system. In many ways, this role is the mirror image of the Data Provider, with the entire Big Data
1174 framework appearing like a Data Provider to the Data Consumer. The activities associated with the Data
1175 Consumer role include the following:

1176 • Search and Retrieve
1177 • Download
1178 • Analyze Locally
1179 • Reporting

- Visualization
- Data to Use for Their Own Processes

The Data Consumer uses the interfaces or services provided by the Big Data Application Provider to get access to the information of interest. These interfaces can include data reporting, data retrieval, and data rendering.

This role will generally interact with the Big Data Application Provider through its access function to execute the analytics and visualizations implemented by the Big Data Application Provider. This interaction may be demand-based, where the Data Consumer initiates the command/transaction and the Big Data Application Provider replies with the answer. The interaction could include interactive visualizations, creating reports, or drilling down through data using business intelligence functions provided by the Big Data Application Provider. Alternately, the interaction may be stream- or push-based, where the Data Consumer simply subscribes or listens for one or more automated outputs from the application. In almost all cases, the Security and Privacy fabric around the Big Data architecture would support the authentication and authorization between the Data Consumer and the architecture, with either side able to perform the role of authenticator/authorizer and the other side providing the credentials. Like the interface between the Big Data architecture and the Data Provider, the interface between the Data Consumer and Big Data Application Provider would also pass through the three distinct phases of initiation, data transfer, and termination.

5 MANAGEMENT FABRIC OF THE NBDRA

The Big Data characteristics of volume, velocity, variety, and variability demand a versatile management platform for storing, processing, and managing complex data Management of Big Data systems should handle both system and data related aspects of the Big Data environment. The Management Fabric of the NBDRA encompasses two general groups of activities: system management and Big Data lifecycle management. System management includes activities such as provisioning, configuration, package management, software management, backup management, capability management, resources management, and performance management. Big Data lifecycle management involves activities surrounding the data lifecycle of collection, preparation/curation, analytics, visualization, and access.

As discussed above, the NBDRA represents a broad range of Big Data systems—from tightly-coupled enterprise solutions integrated by standard or proprietary interfaces to loosely-coupled vertical systems maintained by a variety of stakeholders or authorities bound by agreements, standard interfaces, or de facto standard interfaces. Therefore, different considerations and technical solutions would be applicable for different cases.

5.1 SYSTEM MANAGEMENT

The characteristics of Big Data pose system management challenges on traditional management platforms. To efficiently capture, store, process, analyze, and distribute complex and large datasets arriving or leaving with high velocity, a resilient system management is needed.

As in traditional systems, system management for Big Data architecture involves provisioning, configuration, package management, software management, backup management, capability management, resources management, and performance management of the Big Data infrastructure, including compute nodes, storage nodes, and network devices. Due to the distributed and complex nature of the Big Data infrastructure, system management for Big Data is challenging, especially with respect to the capability for controlling, scheduling, and managing the processing frameworks to perform the scalable, robust, and secure analytics processing required by the Big Data Application Provider. The Big Data infrastructure may contain SAN or NAS storage devices, cloud storage spaces, NoSQL databases, M/R clusters, data analytics functions, search and indexing engines, and messaging platforms. The supporting enterprise computing infrastructure can range from traditional data centers, cloud services, and dispersed computing nodes of a grid. To manage the distributed and complex nature of the Big Data infrastructure, system management relies on the following:

- Standard protocols such as SNMP which are used to transmit status about resources and fault information to the management fabric components
- Deployable agents or management connectors which allow the management fabric to both monitor and also control elements of the framework.

These two items aid in monitoring the health of various types of computing resources and coping with performance and failures incidents while maintaining the quality of service (QoS) levels required by the Big Data Application Provider. Management connectors are necessary for scenarios where the cloud service providers expose management capabilities via APIs. It is conceivable that the infrastructure elements contain autonomic, self-tuning, and self-healing capabilities, thereby reducing the centralized model of system management. In large infrastructures with many thousands of computing and storage nodes, the provisioning of tools and applications should be as automated as possible. Software installation, application configuration, and regular patch maintenance should be pushed out and replicated across the nodes in an automated fashion, which could be done based on the topology knowledge of the

infrastructure. With the advent of virtualization, the utilization of virtual images may speed up the recovery process and provide efficient patching that can minimize downtime for scheduled maintenance.

In an enterprise environment, the management platform would typically provide enterprise-wide monitoring and administration of the Big Data distributed components. This includes network management, fault management, configuration management, system accounting, performance management, and security management.

In a loosely-coupled vertical system, each independent stakeholder is responsible for its own system management, security, and integration. Each stakeholder is responsible for integration within the Big Data distributed system using the interfaces provided by other stakeholders.

5.2 BIG DATA LIFECYCLE MANAGEMENT

Big Data lifecycle management (BDLM) faces more challenges compared to traditional data lifecycle management (DLM), which may require less data transfer, processing, and storage. However, BDLM still inherits the DLM phases in terms of data acquisition, distribution, use, migration, maintenance, and disposition—but at a much bigger processing scale. Big Data Application Providers may require much more computational processing for collection, preparation/curation, analytics, visualization, and access to be able to use the analytic results. In other words, the BDLM activity includes verification that the data are handled correctly by other NBDRA components in each process within the data lifecycle—from the moment they are ingested into the system by the Data Provider, until the data are processed or removed from the system.

The importance of BDLM to Big Data is demonstrated through the following considerations:

- Data volume can be extremely large that may overwhelm the storage capacity, or make storing incoming data prohibitively expensive
- Data velocity, the rate at which data can be captured and ingested into the system, can overwhelm available storage space at a given time. Even with the elastic storage service provided by cloud computing for handling dynamic storage needs, uncontrolled data management may also be unnecessarily costly for certain application requirements.
- Different Big Data applications will likely have different requirements for the lifetime of a piece of data. The differing requirements have implications on how often data must be refreshed so that processing results are valid and useful. In data refreshment, old data are dispositioned and not fed into analytics or discovery programs. At the same time, new data is ingested and taken into account by the computations. For example, real-time applications will need very short data lifetime but a market study of consumers' interest in a product line may need to mine data collected over a longer period of time

Because the task of BDLM can be distributed among different organizations and/or individuals within the Big Data computing environment, coordination of data processing between NBDRA components has greater difficulty in complying with policies, regulations, and security requirements. Within this context, BDLM may need to include the following subactivities:

- **Policy Management:** Captures the requirements for the data lifecycle that allows old data to be dispositioned and new data to be considered by Big Data applications; maintains the migration and disposition strategies that specify the mechanism for data transformation and dispositioning, including transcoding data, transferring old data to lower tier storage for archival purpose, removing data, or marking data as in situ
- **Metadata Management:** Enables BDLM, since metadata are used to store information that governs the management of the data within the system. Essential metadata information includes persistent identification of the data, fixity/quality, and access rights. The challenge is to find the minimum set of elements to execute the required BDLM strategy in an efficient manner.

- **Accessibility Management** Change of data accessibility over time: For example, census data can be made available to the public after 72 years.[6] BDLM is responsible for triggering the accessibility update of the data or sets of data according to policy and legal requirements. Normally, data accessibility information is stored in the metadata.
- **Data Recovery**: BDLM can include the recovery of data that were lost due to disaster or system/storage fault. Traditionally, data recovery can be achieved using regular backup and restore mechanisms. However, given the large volume of Big Data, traditional backup may not be feasible. Instead, replication may have to be designed within the Big Data ecosystem. Depending on the tolerance of data loss—each application has its own tolerance level—replication strategies have to be designed. The replication strategy includes the replication window time, the selected data to be replicated, and the requirements for geographic disparity. Additionally, in order to cope with the large volume of Big Data, data backup and recovery should consider the use of modern technologies within the Big Data Framework Provider.
- **Preservation Management:** The system maintains data integrity so that the veracity and velocity of the analytics process are fulfilled. Due to the extremely large volume of Big Data, preservation management is responsible for disposition-aged data contained in the system. Depending on the retention policy, these aged data can be deleted or migrated to archival storage. In the case where data must be retained for years, decades, and even centuries, a preservation strategy will be needed so the data can be accessed by the provider components if required. This will invoke long-term digital preservation that can be performed by Big Data Application Providers using the resources of the Big Data Framework Provider.

In the context of Big Data, BDLM contends with the Big Data characteristics of volume, velocity, variety, and variability. As such, BDLM and its subactivities interact with other components of the NBDRA as shown in the following examples:

- **System Orchestrator:** BDLM enables data scientists to initiate any combination of processing including accessibility management, data backup/recovery, and preservation management. The process may involve other components of the NBDRA, such as Big Data Application Provider and Big Data Framework Provider. For example, data scientists may want to interact with the Big Data Application Provider for data collection and curation, invoke the Big Data Framework Provider to perform certain analysis, and grant access to certain users to access the analytic results from the Data Consumer.
- **Data Provider:** BDLM manages ingestion of data and metadata from the data source(s) into the Big Data system, which may include logging the entry event in the metadata by the Data Provider
- **Big Data Application Provider:** BDLM executes data masking and format transformations for data preparation or curation purpose
- **Big Data Framework Provider:** BDLM executes basic bit-level preservation and data backup and recovery according to the recovery strategy
- **Data Consumer:** BDLM ensures that relevant data and analytic results are available with proper access control for consumers and software agents to consume within the BDLM policy strategy
- **Security and Privacy Fabric:** Keeps the BDLM up to date according to new security policy and regulations

The Security and Privacy Fabric also uses information coming from BDLM with respect to data accessibility. The Security and Privacy Fabric control access to the functions and data usage produced by the Big Data system. This data access control can be informed by the can use metadata, which is managed and updated by BDLM.

6 SECURITY AND PRIVACY FABRIC OF THE NBDRA

Security and privacy considerations form a fundamental aspect of the NBDRA. This is geometrically depicted in Figure 2 by the Security and Privacy Fabric surrounding the five main components, indicating that all components are affected by security and privacy considerations. Thus, the role of security and privacy is correctly depicted in relation to the components but does not expand into finer details, which may be more accurate but are best relegated to a more detailed security and privacy reference architecture. The Data Provider and Data Consumer are included in the Security and Privacy Fabric since, at the least, they may often nominally agree on security protocols and mechanisms. The Security and Privacy Fabric is an approximate representation that alludes to the intricate interconnected nature and ubiquity of security and privacy throughout the NBDRA. Additional details about the Security and Privacy Fabric are included in the *NIST Interoperability Framework: Volume 4, Security and Privacy* document.

7 CONCLUSION

The NBD-PWG Reference Architecture Subgroup prepared this *NIST Big Data Interoperability Framework: Volume 6, Reference Architecture* to provide a vendor-neutral, technology- and infrastructure-agnostic conceptual model and examine related issues. The conceptual model, referred to as the NIST Big Data Reference Architecture (NBDRA), was a collaborative effort within the Subgroup and with the other NBD-PWG subgroups. The goal of the NBD-PWG Reference Architecture Subgroup is to develop an open reference architecture for Big Data that achieves the following objectives:

- Provides a common language for the various stakeholders
- Encourages adherence to common standards, specifications, and patterns
- Provides consistent methods for implementation of technology to solve similar problem sets
- Illustrates and improves understanding of the various Big Data components, processes, and systems, in the context of a vendor- and technology- agnostic Big Data conceptual model
- Provides a technical reference for U.S. government departments, agencies, and other consumers to understand, discuss, categorize, and compare Big Data solutions
- Facilitates analysis of candidate standards for interoperability, portability, reusability, and extendibility

This document presents the results of the first stage of NBDRA development. The *NIST Big Data Interoperability Framework* will be released in three versions, which correspond to the three stages of the NBD-PWG work. The three stages aim to achieve the following:

Stage 1: Identify the common reference architecture components of Big Data implementations and formulate the technology-independent NBDRA
Stage 2: Define general interfaces between the NBDRA components
Stage 3: Validate the NBDRA by building Big Data general applications through the general interfaces

This document (Version 1) presents the overall NBDRA components and fabrics with high-level description and functionalities.

Version 2 activities will focus on the definition of general interfaces between the NBDRA components by achieving the following:

- Select use cases from the 62 (51 general and 11 security and privacy) submitted use cases or other, to be identified, meaningful use cases
- Work with domain experts to identify workflow and interactions from the System Orchestrator to the rest of the NBDRA components
- Implement small scale, manageable, and well-defined confined environment and model interaction between NBDRA components and fabrics
- Aggregate the common data workflow and interaction between NBDRA components/fabrics and package them into general interfaces

Version 3 activities will focus on validation of the NBDRA through the use of the defined NBDRA interfaces to build general Big Data applications. The validation strategy will include the following:

- Implement the same set of use cases used in Version 2 by using the defined general interfaces
- Identify and implement a few new use cases outside the Version 2 scenarios
- Enhance general NBDRA interfaces through lessons learned from the implementations in Version 3 activities

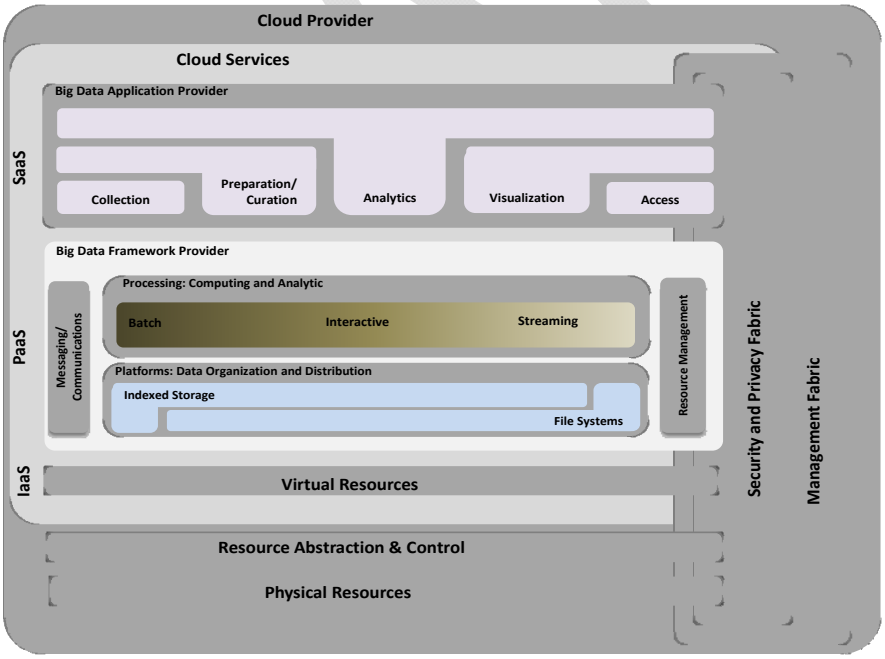
1390 The general interfaces developed during Version 3 activities will offer a starting point for further
1391 refinement by any interested parties and is not intended to be a definitive solution to address all
1392 implementation needs.

1393

Appendix A: Deployment Considerations

The NIST Big Data Reference Architecture is applicable to a variety of business environments and technologies. As a result, possible deployment models are not part of the core concepts discussed in the main body of this document. However, the loosely coupled and distributed natures of Big Data Framework Provider functional components allows it to be deployed using multiple infrastructure elements as described in Section 4.4.1. The two most common deployment configurations are directly on physical resources or on top of an IaaS cloud computing framework. The choices between these two configurations are driven by needs of efficiency/performance and elasticity. Physical infrastructures are typically used to obtain predictable performance and efficient utilization of CPU and I/O bandwidth since it eliminates the overhead and additional abstraction layers typical in the virtualized environments for most IaaS implementations. IaaS cloud based deployments on are typically used when elasticity is needed to support changes in workload requirements. The ability to rapidly instantiate additional processing nodes or framework components allows the deployment to adapt to either increased or decreased workloads. By allowing the deployment footprint to grow or shrink based on workload demands this deployment model can provide cost savings when public or shared cloud services are used and more efficient use and energy consumption when a private cloud deployment is used. Recently, a hybrid deployment model known as Cloud Bursting has become popular. In this model a physical deployment is augmented by either public or private IaaS cloud services. When additional processing is needed to support the workload additional the additional framework component instances are established on the IaaS infrastructure and then deleted when no longer require.

Figure A-1: Big Data Framework Deployment Options



In addition to providing IaaS support cloud providers are now offering Big Data Frameworks under a PaaS model. Under this model the system implementer is freed from the need to establish and manage the complex configuration and deployment typical of many Big Data Framework components. The implementer simply needs to specify the size of the cluster required and the cloud provider manages the provisioning, configuration, and deployment of all the framework components. There are even some nascent offerings for specialized SaaS Big Data applications appearing in the market that implement the Big Data Application Provider functionality within the cloud environment. Figure A-1 illustrates how the

components of the NBDRA might align onto the NIST Cloud Reference architecture[7]. The following sections describe some of the high level interactions required between the Big Data Architecture elements and the Cloud Service Provider elements.

CLOUD SERVICE PROVIDERS

Recent data analytics solutions use algorithms that can utilize and benefit from the frameworks of the cloud computing systems. Cloud computing has essential characteristics such as rapid elasticity and scalability, multi-tenancy, on-demand self-service and resource pooling, which together can significantly lower the barriers to the realization of Big Data implementations.

The **Cloud Service Provider (CSP)** implements and delivers **cloud services**. Processing of a service invocation is done by means of an instance of the service implementation, which may involve the composition and invocation of other services as determined by the design and configuration of the service implementation.

Cloud Service Component

The cloud service component contains the implementation of the cloud services provided by a CSP. It contains and controls the software components that implement the services (but not the underlying hypervisors, host operating systems, device drivers, etc.)

Cloud services can be described in terms of service categories.

Cloud services are also grouped into categories, where each service category is characterized by qualities that are common between the services within the category. The NIST Cloud Computing Reference Model defines the following cloud service categories:

- Infrastructure as a Services (IaaS)
- Platform as a Service (PaaS)
- Software as a Service (SaaS)

Resource Abstraction and Control Component

The Resource Abstraction and Control component is used by cloud service providers to provide access to the physical computing resources through software abstraction. Resource abstraction needs to assure efficient, secure, and reliable usage of the underlying physical resources. The control feature of the component enables the management of the resource abstraction features.

The Resource Abstraction and Control component enables a cloud service provider to offer qualities such as rapid elasticity, resource pooling, on-demand self-service and scale-out. The Resource Abstraction and Control component can include software elements such as hypervisors, virtual machines, virtual data storage, and time-sharing.

The Resource Abstraction and Control component enables control functionality. For example, there may be a centralized algorithm to control, correlate, and connect various processing, storage, and networking units in the physical resources so that together they deliver an environment where IaaS, PaaS or SaaS cloud service categories can be offered. The controller might decide which CPUs/racks contain which virtual machines executing which parts of a given cloud workload, and how such processing units are connected to each other, and when to dynamically and transparently reassign parts of the workload to new units as conditions change.

Security and Privacy and Management Functions

In almost all cases the Cloud Provider will provide elements of the Security, Privacy, and Management functions. Typically the provider will support high level security/privacy functions that control access to the Big Data Applications and Frameworks while the frameworks themselves must control access to their

underlying data and application services. Many times the Big Data specific functions for security and privacy will depend on and must interface with functions provided by the cloud service provider. Similarly, management functions are often split between the Big Data implementation and the Cloud Provider implementations. Here the cloud provider would handle the deployment and provisioning of Big Data architecture elements within its IaaS infrastructure. The cloud provider may provide high level monitoring functions to allow the Big Data implementation to track performance and resource usage of its components. In, many cases the Resource Management element of the Big Data Framework will need to interface to the Cloud Service Provider's management framework to request additional resources.

PHYSICAL RESOURCE DEPLOYMENTS

As stated above deployment on physical resources is frequently used when performance characteristics are paramount. The nature of the underlying physical resource implementations to support Big Data requirements has evolved significantly over the years. Specialized, high performance super computers with custom approaches for sharing resources (memory, CPU, storage) between nodes has given way to shared nothing computing clusters built from commodity servers. The custom super computing architectures almost always required custom development and components to take advantage of the shared resources. The commodity server approach both reduced the hardware investment and allowed the Big Data frameworks to provide higher level abstractions for the sharing and management of resources in the cluster. The Recent trends now involve density, power, cooling optimized server form factors that seek to maximize the available computing resources while minimizing size, power and/or cooling requirements. This approach retains the abstraction and portability advantages of the shared nothing approaches while providing improved efficiency.

Appendix B: Terms and Definitions

NBDRA COMPONENTS

- **Big Data Engineering:** Advanced techniques that harness independent resources for building scalable data systems when the characteristics of the datasets require new architectures for efficient storage, manipulation, and analysis.
- **Data Provider:** Organization or entity that introduces information feeds into the Big Data system for discovery, access, and transformation by the Big Data system.
- **Big Data Application Provider:** Organization or entity that executes a generic vertical system data lifecycle, including: (a) data collection from various sources, (b) multiple data transformations being implemented using both traditional and new technologies, (c) diverse data usage, and (d) data archiving.
- **Big Data Framework Provider:** Organization or entity that provides a computing fabric (such as system hardware, network, storage, virtualization, and computing platform) to execute certain Big Data applications, while maintaining security and privacy requirements
- **Data Consumer:** End users or other systems that use the results of data applications.
- **System Orchestrator:** Organization or entity that defines and integrates the required data transformations components into an operational vertical system.

OPERATIONAL CHARACTERISTICS

- Interoperability: The capability to communicate, to execute programs, or to transfer data among various functional units under specified conditions.
- Portability: The ability to transfer data from one system to another without being required to recreate or reenter data descriptions or to modify significantly the application being transported.
- Privacy: The assured, proper, and consistent collection, processing, communication, use and disposition of data associated with personal information (PI) and personally-identifiable information (PII) throughout its lifecycle.
- Security: Protecting data, information, and systems from unauthorized access, use, disclosure, disruption, modification, or destruction in order to provide:
  - Integrity: guarding against improper data modification or destruction, and includes ensuring data nonrepudiation and authenticity
  - Confidentiality: preserving authorized restrictions on access and disclosure, including means for protecting personal privacy and proprietary data
  - Availability: ensuring timely and reliable access to and use of data
- Elasticity: The ability to dynamically scale up and down as a real time response to the workload demand. Elasticity will depend on the Big Data system, but adding or removing "software threads" and "virtual or physical servers" are two widely used scaling techniques. Many types of workload demands drive elastic responses, including Web based users, software agents, and periodic batch jobs.
- Persistence: The placement/storage of data in a medium design to allow its future access.

PROVISIONING MODELS

- Infrastructure as a Service (IaaS): The capability provided to the consumer to provision processing, storage, networks, and other fundamental computing resources where the consumer is able to deploy and run arbitrary software, which can include operating systems and applications. The consumer does not manage or control the underlying cloud infrastructure but

1531 has control over operating systems, storage, deployed applications, and possibly limited control
1532 of select networking components (e.g., host firewalls).[8]
1533 • Platform as a Service (PaaS): The capability provided to the consumer to deploy onto the cloud
1534 infrastructure consumer-created or acquired applications created using programming languages
1535 and tools supported by the provider. The consumer does not manage or control the underlying
1536 cloud infrastructure including network, servers, operating systems, or storage, but has control
1537 over the deployed applications and possibly application hosting environment configurations.
1538 (Source: NIST CC Definition)
1539 • Software as a Service (SaaS): The capability provided to the consumer to use applications
1540 running on a cloud infrastructure. The consumer does not manage or control the underlying
1541 cloud infrastructure including network, servers, operating systems, storage, or even individual
1542 application capabilities, with the possible exception of limited user-specific application
1543 configuration settings. (Source: NIST CC Definition)
1544

Appendix C: Examples of Big Data Organization Approaches

This appendix provides an overview of several common Big Data Organization Approaches. The reader should keep in mind that new and innovative approaches are emerging regularly and that some of these approaches are hybrid models that combine features of several indexing techniques (e.g., relational and columnar, or relational and graph).

RELATIONAL STORAGE MODELS

This model is perhaps the most familiar to folks as the basic concept has existed since the 1950s and the Structured Query Language (SQL) is a mature standard for manipulating (search, insert, update, delete) relational data. In the relational model, data is stored as rows with each field representing a column organized into Table based on the logical data organization. The problem with relational storage models and Big Data is the join between one or more tables. While the size of 2 or more tables of data individually might be small the join (or relational matches) between those tables will generate exponentially more records. The appeal of this model for organizations just adopting Big Data is its familiarity. The pit falls are some of the limitations and more importantly the tendency to adopt standard RDBMS practices (high normalization, detailed and specific indexes) and performance expectations

Big data implementations of relational storage models are relatively mature and have been adopted by a number of organizations. They are also maturing very rapidly with new implementations focusing on improved response time. Many Big Data implementations take a brute force approach to scaling relational queries. Essentially, queries are broken into stages but more importantly processing of the input tables is distributed across multiple nodes (often as a Map/Reduce job). The actual storage of the data can be flat files (delimited or fixed length) where each record/line in the file represents a row in a table. Increasingly however these implementations are adopting binary storage formats optimized for distributed file systems. These formats will often use block level indexes and column oriented organization of the data to allow individual fields to be accessed in records without needing to read the entire record. Despite this, most Big Data Relational storage models are still "batch oriented" systems designed for very complex queries which generate very large intermediate cross-product matrices from joins so even the simplest query can required 10s of seconds to complete. There is significant work going on and emerging implementations that are seeking to provide a more interactive response and interface.

Early implementations only provided limited data types and little or no support for indexes. However, most current implementations have support for complex data structures and basic indexes. However, while the query planners/optimizers for most modern RDBMS systems are very mature and implement cost-based optimization through statistics on the data the query planners/optimizers in many Big Data implementations remain fairly simple and rule-based in nature. While for batch oriented systems this generally acceptable (since the scale of processing the Big Data in general can be orders of magnitude more an impact) any attempt to provide interactive response will need very advanced optimizations so that (at least for queries) only the most likely data to be returned is actually searched. This of course leads to the single most serious draw back with many of these implementations. Since distributed processing and storage are essential for achieving scalability these implementations are directly limited by the CAP (Consistency, Availability, and Partition Tolerance) theorem. Many in fact provide what is generally referred to as a t-eventual consistency which means that barring any updates to a piece of data all nodes in the distributed system will eventually return the most recent value. This level of consistency is typically fine for Data Warehousing applications where data is infrequently updated and updates are generally done in bulk. However, transaction oriented databases typically require some level of ACID (Atomicity, Consistency, Isolation, Durability) compliance to insure that all transactions are handled reliably and conflicts are resolved in a consistent manner. There are a number of both industry and open source

initiatives looking to bring this type of capability to Big Data relational storage frameworks. One approach is to essentially layer a traditional RDBMS on top of an existing distributed file system implementation. While vendors claim that this approach means that the overall technology is mature a great deal of research and implementation experience is needed before the complete performance characteristics of these implementations are known.

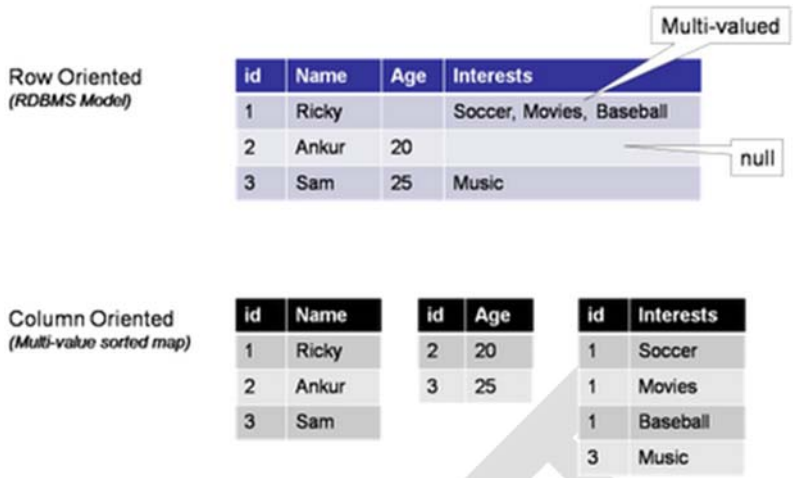
Key-Value Storage Models

Key-value stores are one of the oldest and mature data indexing models. In fact, the principles of key value stores underpin all the other storage and indexing models. From a Big Data perspective, these stores effectively represent random access memory models. While the data stored in the values can be arbitrarily complex in structure all the handling of that complexity must be provided by the application with the storage implementation often providing back just a pointer to a block of data. Key-Value stores also tend to work best for 1-1 relationships (e.g., each key relates to a single value) but can also be effective for keys mapping to lists of homogeneous values. When keys map multiple values of heterogeneous types/structures or when values from one key need to be joined against values for a different or the same key then custom application logic is required. It is the requirement for this custom logic that often prevents Key-Value stores from scaling effectively for certain problems. However, depending on the problem certain processing architectures can make effective use of distributed key-value stores. Key-value stores generally deal well with updates when the mapping is one to one and the size/length of the value data does not change. The ability of key-value stores to handle inserts is generally dependent on the underlying implementation. Key-value stores also generally require significant effort (either manual or computational) to deal with changes to the underlying data structure of the values.

Distributed key-value stores are the most frequent implementation utilized in Big Data applications. One problem that must always be addressed (but is not unique to key-value implementations) is the distribution of keys across over the space of possible key values. Specifically, keys must be chosen carefully to avoid skew in the distribution of the data across the cluster. When data is heavily skewed to a small range it can result in computation hot spots across the cluster if the implementation is attempting to optimize data locality. If the data is dynamic (new keys being added) for such an implementation then it is likely that at some point the data will require rebalancing across the cluster. Non-locality optimizing implementations employ various sorts of hashing, random, or round-robin approaches to data distribution and don't tend to suffer from skew and hot spots. However, they perform especially poorly on problems requiring aggregation across the data set.

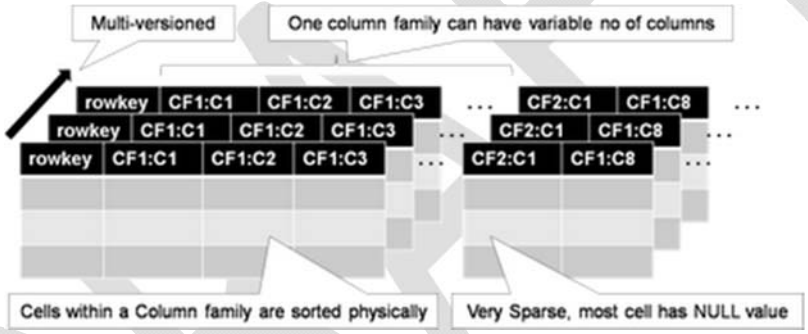
Columnar Storage Models

Much of the hype associated with Big Data came with the publication of the Big Table paper in 2006 (Chang, et al., 2006) but column oriented storage models like BigTable are not new to even Big Data and have been stalwarts of the data warehousing domain for many years. Unlike traditional relational data that store data by rows of related values, columnar stores organize data in groups of like values. The difference here is subtle but in relational databases an entire group of columns are tied to some primary-key (frequently one or more of the columns) to create a record. In columnar, the value of every column is a key and like column values point to the associated rows. The simplest instance of a columnar store is little more than a key-value store with the key and value roles reversed. In many ways, columnar data stores look very similar to indexes in relational databases. Figure 5 below shows the basic differences between row oriented and column oriented stores.



1634 ***Figure B-1: Differences Between Row Oriented and Column Oriented Stores***

1635 In addition, implementations of columnar stores that follow the BigTable model introduce an additional
1636 level of segmentation beyond the table, row, and column model of the relational model. That is called the
1637 column family. In those implementations rows have a fixed set of column families but within a column
1638 family each row can have a variable set of columns. This is illustrated in Figure 6 below.



1639 ***Figure B-2: Column Family Segmentation of the Columnar Stores Model***

1640 The key distinction in the implementation of columnar store over relational stores is that data is high de-
1641 normalized for column stores and that while for relational stores every record contains some value
1642 (perhaps NULL) for each column, in columnar store the column is only present if there is data for one or
1643 more rows. This is why many column oriented stores are referred to as sparse storage models. Data for
1644 each column family is physically stored together on disk sorted by rowed, column name and timestamp.
1645 The last (timestamp) is there because the BigTable model also includes the concept of versioning. Every,
1646 RowKey, Column Family, Column triple is stored with either a system generated or user provided
1647 Timestamp. This allows users to quickly retrieve the most recent value for a column (the default), the
1648 specific value for a column by timestamp, or all values for a column. The last is most useful because it
1649 permits very rapid temporal analysis on data in a column.

1650 Because data for a given column is stored together two key benefits are achieved. First aggregation of the
1651 data in that column requires only the values for that column to be read. Conversely in a relational system
1652 the entire row (at least up to the column) needs to be read (which if the row is long and the column at the
1653 end it could be lots of data). Secondly, updates to a single column do not require the data for the rest of
1654 the row to be read/written. Also, because all the data in a column is uniform, data can be compressed
1655 much more efficiently. Often only a single copy of the value for a column is stored followed by the row
1656 keys where that value exists. And while deletes of an entire column is very efficient, deletes of an entire

record are extremely expensive. This is why historically column oriented stores have been applied to OLAP style applications while relational stores were applied to OLTP requirements.

Recently, security has been a major focus of existing column implementations primarily due to the release by the National Security Agency (NSA) of its BigTable implementation to the open source community. A key advantage of the NSA implementation and other recently announced implementations is the availability of security controls at the individual cell level. With these implementations a given user might have access to only certain cells in group based potentially based on the value of those or other cells.

There are several very mature distributed column oriented implementations available today from both open source groups and commercial foundations. These have been implemented and operational across a wide range of businesses and government organizations. Emerging are hybrid capabilities that implement relational access methods (e.g., SQL) on top of BigTable/Columnar storage models. In addition, relational implementations are adopting columnar oriented physical storage models to provide more efficient access for Big Data OLAP like aggregations and analytics.

Document

Document storage approaches have been around for some time and popularized by the need to quickly search large amounts of unstructured data. Modern, document stores have evolved to include extensive search and indexing capabilities for structured data and metadata and why they are often referred to as semi-structured data stores. Within a document-oriented data store each "document" encapsulates and encodes the metadata, fields, and any other representations of that record. While somewhat analogous to a row in a relational table one-reason document stores evolved and have gained in popularity is that most implementations do not enforce a fixed or constant schema. While best practices hold that groups of documents should be logically related and contain similar data there is no requirement that they be alike or that any two documents even contain the same fields. That is one reason that document stores are frequently popular for data sets which have sparsely populated fields since there is far less overhead normally than traditional RDBMS systems where null value columns in records are actually stored. Groups of documents within these types of stores are generally referred to as collections and like key-value stores some sort of unique key references each document.

In modern implementations documents can be built of arbitrarily nested structures and can include variable length arrays and in some cases executable scripts/code (which has significant security and privacy implications). Most document-store implementations also support additional indexes on other fields or properties within each document with many implementing specialized index types for sparse data, geospatial data, and text.

When modeling data into document-stores the preferred approach is to de-normalize the data as much as possible and embed all one-to-one and most one-to-many relationships within a single document. This allows for updates to documents to be atomic operations which keep referential integrity between the documents. The most common case where references between documents should be use is when there are data elements that occur frequently across sets of documents and whose relationship to those documents is static. As an example, the publisher of a given book edition does not change and there are far fewer publishers than there are books. It would not make sense to embed all the publisher information into each book document. Rather the book document would contain a reference to the unique key for the publisher. Since for that edition of the book the reference will never change and so there is no danger of loss of referential integrity. Thus information about the publisher (address for example) can be updated in a single atomic operation the same as the book. Where this information embedded it would need to be updated in every book document with that publisher.

In the Big Data realm document stores scale horizontally through the use of partitioning or sharding to distribute portions of the collection across multiple nodes. This partitioning can be round-robin based insuring an even distribution of data or content/key based so that data locality is maintained for similar

data. Depending on the application required the choice of partitioning key like with any data base can have significant impacts on performance especially where aggregation functions are concerned.

There are no standard query languages for document store implementations with most using a language derived from their internal document representation (e.g., JSON, XML).

Graph

While social networking sites like Facebook and LinkedIn have certainly driven the visibility of and evolution of graph stores (and processing as discussed below), graph stores have been a critical part of many problem domains from military intelligence and counter terrorism to route planning/navigation and the semantic web for years. Graph stores represent data as a series of nodes, edges, and properties on those. Analytics against graph stores include very basic shortest path and page ranking to entity disambiguation and graph matching.

Graph databases typically store two types of objects nodes and relationships as show in Figure 7 below. Nodes represents objects in the problem domain that are being analyzed be they people, places, organizations, accounts, or other objects. Relationships describe those objects in the domain relate to each other. Relationships can be nondirectional/bidirectional but are typically expressed as unidirectional in order to provide more richness and expressiveness to the relationships. Hence, between two people nodes where they are father and son there would be two relationships. One "is father of" going from the father node to the son node, and the other from the son to the father of "is son of". In addition, nodes and relationships can have properties or attributes. This is typically descriptive data about the element. For people it might be name, birthdate, or other descriptive quality. For locations it might be an address or geospatial coordinate. For a relationship like a phone call it could be the date, time of the call, and the duration of the call. Within graphs relationships are not always equal or have the same strength. Thus relationship often has one or more weight, cost, or confidence attributes. A strong relationship between people might have a high weight because they have known each other for years and communicate every day. A relationship where two people just met would have a low weight. The distance between nodes (be it a physical distance or a difficulty) is often expressed as a cost attribute on a relation in order to allow computation of true shortest paths across a graph. In military intelligence applications, relationships between nodes in a terrorist or command and control network might only be suspected or have not been completely verified so those relationships would have confidence attributes. Also, properties on nodes may also have confidence factors associated with them although in those cases the property can be decomposed into its own node and tied with a relationship. Graph storage approaches can actually be viewed as a specialized implementation of a document storage scheme with two types of documents (nodes and relationships). In addition, one of the most critical elements in analyzing graph data is locating the node or edge in the graph where the analysis is to begin. To accomplish this most graph databases implement indexes on the node or edge properties. Unlike, relational and other data storage approaches most graph databases tend to use artificial/pseudo keys or guides to uniquely identify nodes and edges. This allows attributes/properties to be easily changed due to both actual changes in the data (someone changed their name) or as more information is found out (e.g., a better location for some item or event) without needing to change the pointers two/from relationships.

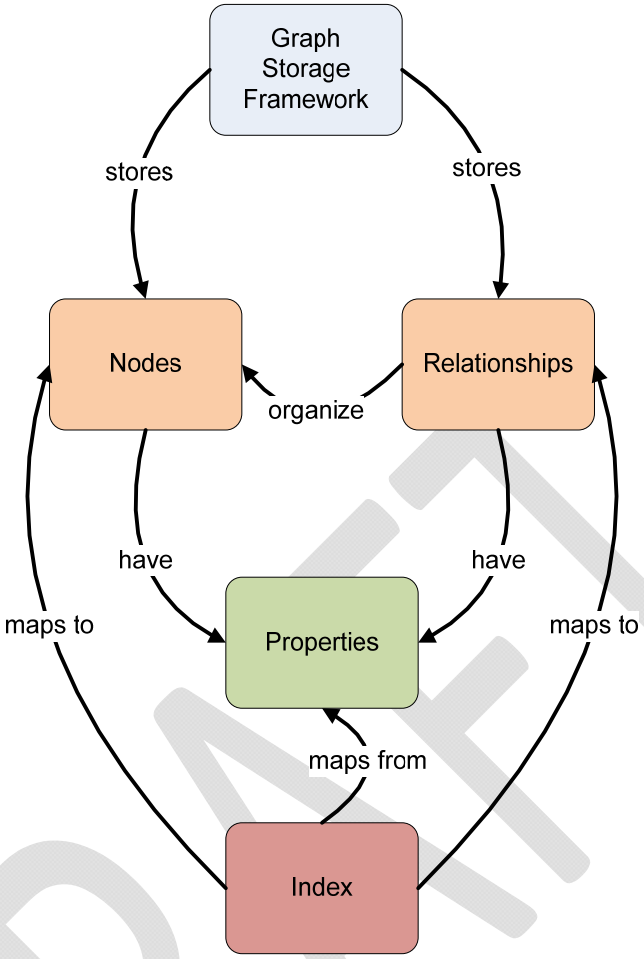


Figure B-3: Object Nodes and Relationships of Graph Databases

The problem with graphs in the Big Data realm is that they grow to be too big to fit into memory on a single node and by their typically chaotic nature (few real world graphs follow well defined patterns) makes their partitioning for a distributed implementation problematic. While distance between or closeness of nodes would seem like a straight forward partitioning approach there are multiple issues which must be addressed. First, would be balancing of data. Graphs often tend to have large clusters of data very dense in a given area thus leading to essentially imbalances and hot spots in processing. Second, no matter how the graph is distributed, there are connections (edges) that will cross the boundaries. That typically requires that nodes know about or how to access the data on other nodes and requires inter-node data transfer or communication. This makes the choice of processing architectures for graph data especially critical. Architectures that do not have inter-node communication/messaging tend not to work well for most graph problems. Typically, distributed architectures for processing graphs assign chunks of the graph to nodes then the nodes use messaging approaches to communicate changes in the graph or the value of certain calculations along a path.

Even small graphs quickly elevate into the realm of Big Data when one is looking for patterns or distances across more than one or two degrees of separation between nodes. Depending on the density of the graph, this can quickly cause a combinatorial explosion in the number of conditions/patterns that need to be tested.

A specialized implementation of a graph store known as the Resource Description Framework (RDF) is part of a family of specifications from the World Wide Web Consortium (W3C) that is often directly

associated with Semantic Web and associated concepts. RDF triples as they are known consist of a Subject (Mr. X), a predicate (lives at), and an object (Mockingbird Lane). Thus a collection of RDF triples represents and directed labeled graph. The contents of RDF stores are frequently described using formal ontology languages like OWL or the RDF Schema (RDFS) language, which establish the semantic meanings and models of the underlying data. To support better horizontal integration (Smith, Malyuta, Mandirck, Fu, Parent, & Patel, 2012) of heterogeneous data sets extensions to the RDF concept such as the Data Description Framework (DDF) (Yoakum-Stover & Malyuta, 2008) have been proposed which add additional types to better support semantic interoperability and analysis.

Graph data stores currently lack any form of standardized APIs or query languages. However, the W3C has developed the SPARQL query language for RDF which is currently in a recommendation status and there are several frameworks such as Sesame which are gaining popularity for working with RDF and other graph oriented data stores.

Appendix D: Acronyms

APIs	application programming interface
CIA	confidentiality, integrity, and availability
CRUD	create/read/update/delete
CSP	Cloud Service Provider
DNS	Domain Name Server
GRC	governance, risk, and compliance
HTTP	HyperText Transfer Protocol
I/O processing	Input/Output Processing
IaaS	Infrastructure as a Service
IT	Information Technology
LAN	Local Area Network
MAN	Metropolitan Area Network
NaaS	Network as a Service
NBD-PWG	NIST Big Data Public Working Group
NBDRA	NIST Big Data Reference Architecture
NIST	National Institute of Standards and Technology
PaaS	Platform as a Service
PII	Personally Identifiable Information
SaaS	Software as a Service
SANs	Storage Area Networks
SLAs	Service-level Agreements
VM	Virtual Machine
WAN	Wide Area Network
WiFi	

Appendix E: Resources and References

GENERAL RESOURCES

The following resources provide additional information related to Big Data architecture.

[1] Office of the White House Press Secretary, "Obama Administration Unveils "Big Data" Initiative", *White House Press Release* (29 March 2012)
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http://www.whitehouse.gov/sites/default/files/microsites/ostp/big_data_fact_sheet_final_1.pdf

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http://www.nist.gov/itl/ssd/is/big-data.cfm

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[7] Gartner, "The Importance of 'Big Data': A Definition",
http://www.gartner.com/DisplayDocument?id=2057415&ref=clientFriendlyUrl

[8] Hilbert, Martin and Lopez, Priscilla, "The World's Technological Capacity to Store, Communicate, and Compute Information", Science, 01 April 2011

[9] U.S. Department of Defense, "Reference Architecture Description", June 2010,
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[2] "Reference Architecture Description", U.S. Department of Defense, June 2010. http://dodcio.defense.gov/Portals/0/Documents/DIEA/Ref_Archi_Description_Final_v1_18Jun10.pdf.

[3] Colella, Phillip, Defining software requirements for scientific computing. Slide of 2004 presentation included in David Patterson's 2005 talk. 2004. http://www.lanl.gov/orgs/hpc/salishan/salishan2005/davidpatterson.pdf

[4] Patterson, David; Yelick, Katherine. Dwarf Mind. A View From Berkeley. http://view.eecs.berkeley.edu/wiki/Dwarf_Mine

[5] Leslie G. Valiant, A bridging model for parallel computation, Communications of the ACM, Volume 33 Issue 8, Aug. 1990

[6] United States Census Bureau, The "72-Year Rule." https://www.census.gov/history/www/genealogy/decennial_census_records/the_72_year_rule_1.html. Accessed March 3, 2015.

[7] NIST SP 500-292, *NIST Cloud Computing Reference Architecture*. September 2011. http://www.nist.gov/customcf/get_pdf.cfm?pub_id=909505

[8] http://csrc.nist.gov/publications/nistpubs/800-145/SP800-145.pdf (The NIST Definition of Cloud Computing, Special Publication 800-145, September 2011)