Big Data Use Cases and Requirements

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Abstract

We formed a community of interest from industry, academia, and government, with the goal of developing a consensus set of Big Data requirements across all stakeholders. The major activities were gathering various use cases from diversified application domains and extracting requirements. Initially we developed a use case template with 26 fields, and these were completed for 51 areas. They were spread over application sectors as follows: Government Operations (4), Commercial (8), Defense (3), Healthcare and Life Sciences (10), Deep Learning and Social Media (6), The Ecosystem for Research (4), Astronomy and Physics (5), Earth, Environmental and Polar Science (10), Energy (1). These are, of course, only representative, and miss many important cases; but they form an interesting set for initial study. After gathering the use case. Those specific requirements were then mapped to broad characteristics, which were motivated by the structure of the NIST PWG reference architecture. These characteristics were Data sources, Data transformation, Capability infrastructure, Data Consumer, Security & Privacy, Lifecycle management and "Other" where the latter catch-all largely included mobile access. Then we aggregated all the 439 specific requirements into 35 high-level generalized requirements, which are vendor-neutral and technology agnostic.

1 Introduction

On June 19, 2013, the NIST Big Data Public Working Group (NBD-PWG) was launched with participation from industry, academia, and government from across the nation. The scope of NBD-PWG involves forming a community of interests from all sectors—including industry, academia, and government—with the goal of developing a consensus on definitions, taxonomies, secure reference architectures, and a technology 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.

NBD-PWG currently has created five subgroups: Definitions and Taxonomies, Security and Privacy, Reference Architecture, Technology Roadmap plus the Use Case and Requirements subgroup whose work is discussed here.

The initial focus of the NBD-PWG Use Case and Requirements Subgroup was to form a community of interest from industry, academia, and government, with the goal of developing a consensus list of big data requirements across all stakeholders. This included gathering and understanding various use cases from diversified application domains.

Tasks assigned to the subgroup include the following:

- Gather input from all stakeholders regarding big data requirements. A goal that turned into gathering use cases
- Analyze/prioritize a list of challenging general requirements derived from use cases that may delay or prevent adoption of big data deployment.
- Develop a comprehensive list of big data requirements.

This report was produced by an open collaborative process involving weekly telephone conversations and information exchange using the NIST document system. The 51 use cases came from participants in the calls (subgroup members), and from others informed of the opportunity to contribute. The activity culminated in a public meeting September 30 2013 at NIST.

The use cases are organized into the nine broad sectors/areas (application domains) listed below with examples and number of use cases in parentheses:

- Government Operation (4): National Archives and Records Administration, Census
 Bureau
- **Commercial (8):** Finance in Cloud, Cloud Backup, Mendeley (Citations), Netflix, Web Search, Digital Materials, Cargo Shipping (as in UPS)
- **Defense (3):** Sensors, Image Surveillance, Situation Assessment
- Healthcare and Life Sciences (10): Medical Records, Graph and Probabilistic Analysis, Pathology, Bioimaging, Genomics, Epidemiology, People Activity Models, Biodiversity
- **Deep Learning and Social Media (6)** Self-driving cars, Geolocate Images, Twitter, Crowd Sourcing, Network Science, NIST Benchmark Datasets
- **Ecosystem for Research (4):** Metadata, Collaboration, Language Translation, Light Source Experiments
- Astronomy and Physics (5): Sky Surveys (and comparisons to simulation), LHC at CERN, Belle Accelerator II in Japan
- Earth, Environmental, and Polar Science (10): Radar Scattering in Atmosphere, Earthquake, Ocean, Earth Observation, Ice Sheet Radar Scattering, Earth Radar Mapping, Climate Simulation Datasets, Atmospheric Turbulence Identification, Subsurface Biogeochemistry (microbes to watersheds), AmeriFlux and FLUXNET Gas Sensors
- Energy(1): Smart Grid

Many presentations have been given [1-6] on the use case activity and follow-on analysis has been presented identifying common patterns [7, 8] and mapping into the well-known Apache [9] software environment [10, 11].

2 Use Cases

The working group began by defining a use case template, shown in Table 1. The template was valuable for gathering consistent information, thus supporting analysis and comparison of the use cases. However, the use cases are described in varying levels of detail. In addition, while some use cases are described in (mostly) qualitative terms, others include detailed quantitative data/metrics. The individual use cases may be downloaded from the NIST document library [12]. In addition, all 51 use cases are compiled in a single document [13] and are published by NIST as part of their Big Data document collection [14]. We stress that all use cases have been submitted openly, and no significant editing has been performed. There are differences in scope and interpretation, but the benefits of free and open submission outweigh those of greater uniformity.

Use Case Title			
Vertical (area)			
Author/Company/Er	nail		
Actors/Stakeholders their roles and responsibilities	and		
Goals			
Use Case Description	า		
	Compu	ute(System)	
Current	Storage	e	
Solutions	Networ	king	
	Softwa	re	
Big Data Data S		ource uted/centralized)	

Table 1: NBD (NIST Big Data) Requirements WG Use Case Template Aug 11 2013

	Volume	e (size)	
	Velocity	У	
	(e.g. re	al time)	
	Variety		
	(multipl	e datasets, mashup)	
	Variabi	lity (rate of change)	
Big Data Science	Veracit semant	y (Robustness Issues, ics)	
(collection,	Visualiz	ation	
curation, analysis,	Data Q	uality (syntax)	
action)	Data Ty	/pes	
	Data A	nalytics	
Big Data Specific			
Challenges (Gaps)			
Big Data Specific			
Challenges in Mobilit	y		
Security & Privacy			
Requirements			
Highlight issues for			
generalizing this use	case		
(e.g. for ref. architect	ture)		
More Information (UR	Ls)		
Note: <additional co<="" th=""><td>mments></td><td>·</td><td></td></additional>	mments>	·	
Notes to preparer: No	o proprie	tary or confidential info	rmation should be included.
Please ADD picture of	of operat	ion or data architectur	e of application below table

The 51 use cases are given in Table 2 divided into 9 categories and listing counts of requirements derived by the process described in Section 3. Table 2 also gives the institutional source of each use case. Note these use cases have a higher fraction of scientific research than a sample that reflected actual sizes of data. For example probably the largest science data sizes are <~100 petabytes (use case 39 – LHC) which is <0.00002 of the size of digital universe of shared electronic data [15, 16]. The latter are dominated by data from commercial sector in Table 2 with only 8 of 51 use cases. The 51 use cases are organized into the nine application domains introduced in section 1. For some domains, multiple similar big data applications are presented, providing a more complete view of big data requirements in that domain. The full report of the working group [14] has substantial detail on each use case including:

- The completed use case template of Table 1
- A relatively uniform summary of each use case consisting of 3 components: Application Overview, Current processing approach and Futures of application and analysis.
- Diagrams and figures illustrating some of use cases
- Summary of key properties for each use case: Data Volume, Velocity, Variety and Software Analytics

#	Use Case	G is # Generic Requirements				# S ∋qu	•			
		Source	G	S	Τ	С	U	Ρ	L.	0
	Government Operation									
1	Census 2010 and 2000 - Title 13 Big Data	NARA	8	1		1		1	5	
2	National Archives and Records Administration Accession NARA, Search, Retrieve, Preservation	NARA	10	5	5	2	3	1	4	1
3	Statistical Survey Response Improvement (Adaptive Design)	U.S. Census Bureau	9	1	1	1	1	2	1	1
4 Non-Traditional Data in Statistical Survey Response Improvement (Adaptive Design)		U.S. Census Bureau	4		1	1	1	1	1	
	Commercial									

5			1	r	T	1	1	1	r –	
	Cloud Eco-System, for Financial Industries (Banking, Securities & Investments, Insurance) transacting business within the United	Compliance Partners,	1	1	1			1		1
	States	LLC	'		L '			1		
6	Mendeley - An International Network of Research	Mendeley	13	2	3	6	2	1	4	1
	Netflix Movie Service	Indiana University	21	2	5	6	2	1	1	1
8	Web Search	Indiana University	15	3	2	1	3	2	2	1
0		Compliance Partners,	10	3	2		3	2	2	-
9	IaaS (Infrastructure as a Service) Big Data Business Continuity & Disaster Recovery (BC/DR) Within A Cloud Eco-System	LLC			2	2		1		
10	Cargo Shipping	MaCT USA	7	1	2	1		1		
	Materials Data for Manufacturing		8	3	2		2	2	1	
		R&R Data Services DoE LBNL	8 14	3	4	8	2	2	2	1
12	Simulation driven Materials Genomics Defense	DOE LBINL	14	Z	4	8		2	Z	
12		Data Tactics	7	1	2	1	1	1	<u> </u>	-
13		Data factics	/	1	2		1			
14	Object identification and tracking from Wide Area Large	Data Tactics	10	1	1	3	2	1	1	
14	Format Imagery (WALF) Imagery or Full Motion Video (FMV) - Persistent Surveillance	Data factics	10	1	L '	3	2	1	1	
15		Data Tactica	11	3	1	3	1	1	1	
15	Intelligence Data Processing and Analysis	Data Tactics		3		3		11		
17	Healthcare and Life Sc		11	I r	2	4	1	I r	2	1
	Electronic Medical Record (EMR) Data	Indiana University	15	5	2	4	1	5	3	1
	Pathology Imaging/digital pathology	Emory University	15	4	3	4	1	1	1	1
18	Computational Bioimaging	Doe LBNL	11	2	4	4	1	1	1	_
19	Genomic Measurements	NIST	15	3	2	3	1	1	-	1
	Comparative analysis for metagenomes and genomes	Doe LBNL	12	5	6	1	5	3	3	
	Individualized Diabetes Management	Indiana University	12	6	6	5	1	2	3	1
	Statistical Relational Artificial Intelligence for Health Care	Indiana University	11	6	5	5	1	1	1	
23	World Population Scale Epidemiological Study	Virginia Tech	12	3	3	5	1	2	1	
24	Social Contagion Modeling for Planning, Public Health and Disaster Management	Virginia Tech	13	3	3	5	2	2	3	1
25	Biodiversity and LifeWatch	University of Amsterdam	10	6	7	2	3	2	5	
	Deep Learning and Socia					•	•			
26	Large-scale Deep Learning	Stanford University	3		1	3	1	1		
27	Organizing large-scale, unstructured collections of consumer photos	Indiana University	8	1	2	1	1	1		
28	Truthy: Information diffusion research from Twitter Data	Indiana University	13	5	1	4	3	1	1	1
	Crowd Sourcing in the Humanities as Source for Big and	Max-Planck-Institute		Ŭ		<u> </u>	Ŭ		<u> </u>	-
$2 \circ$			2		2			1		
29	Dynamic Data	Nijmegen	3		2			1		
29 30	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics	Nijmegen Virginia Tech	3 9	2	4	5	1			
30	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology	Virginia Tech	9	-	4		-			
	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards	Virginia Tech NIST		2	-	5 1	1	1		
30 31	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Reso	Virginia Tech NIST earch	9	2	4	1	-	1		
30	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC	Virginia Tech NIST	9	-	4		-			
30 31	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Reso	Virginia Tech NIST earch	9	2	4	1	1	1	1	
30 31 32	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <-> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based	Virginia Tech NIST earch UNC Chapel Hill	9	2	4	1	1	1	1	
30 31 32 33 34	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Res DataNet Federation Consortium DFC The 'Discinnet process', metadata <-> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST	9	2 2 1	4	1 2 1	1	1	1	
30 31 32 33 34	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DOE LBNL	9	2 2 1	4 1 2	1 2 1 1	1	1 2 1	1	
30 31 32 33 34 35	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines Astronomy and Physical Comparison of	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DOE LBNL sics	9 5 1	2 2 1	4 1 2 1	1 2 1 1	1	1 2 1	1	
30 31 32 33 34	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DoE LBNL sics Caltech	9	2 2 1	4 1 2	1 2 1 1	1	1 2 1	1	
30 31 32 33 34 35	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Rese DataNet Federation Consortium DFC The 'Discinnet process', metadata <> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines Astronomy and Physe Catalina Real-Time Transient Survey (CRTS): a digital,	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DOE LBNL sics Caltech DoE Argonne, University of	9 5 1	2 2 1 1 2	4 1 2 1	1 2 1 1	1	1 2 1		
30 31 32 33 34 35 36 37	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <-> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines Astronomy and Phys Catalina Real-Time Transient Survey (CRTS): a digital, panoramic, synoptic sky survey DOE Extreme Data from Cosmological Sky Survey and Simulations	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DOE LBNL sics Caltech DoE Argonne, University of Washington	9 5 1 1 3 6	2 1 1 2 1	4 1 2 1 2 1	1 2 1 1 1 2 2	1	1 2 1		
30 31 32 33 34 35 36 37 38	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <-> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines Astronomy and Phys Catalina Real-Time Transient Survey (CRTS): a digital, panoramic, synoptic sky survey DOE Extreme Data from Cosmological Sky Survey and Simulations Large Survey Data for Cosmology	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DoE LBNL sics Caltech DoE Argonne, University of Washington DoE LBNL	9 5 1 1 3 6 7	2 1 1 2 1 1 1 1	4 1 2 1 2 1 2	1 2 1 1 1 2 2 3	1	1 2 1		
30 31 32 33 34 35 36 37	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <-> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines Astronomy and Phys Catalina Real-Time Transient Survey (CRTS): a digital, panoramic, synoptic sky survey DOE Extreme Data from Cosmological Sky Survey and Simulations Large Survey Data for Cosmology Particle Physics: Analysis of LHC Large Hadron Collider Data:	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DoE LBNL sics Caltech DoE Argonne, University of Washington DoE LBNL DoE LBNL DoE BNL, FNAL, LBNL,	9 5 1 1 3 6	2 1 1 2 1 1 1 1	4 1 2 1 2 1	1 2 1 1 1 2 2	1	1 2 1		
30 31 32 33 34 35 36 37 38 39	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <-> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines Astronomy and Phys Catalina Real-Time Transient Survey (CRTS): a digital, panoramic, synoptic sky survey DOE Extreme Data from Cosmological Sky Survey and Simulations Large Survey Data for Cosmology Particle Physics: Analysis of LHC Large Hadron Collider Data: Discovery of Higgs particle	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DoE LBNL Sics Caltech DoE Argonne, University of Washington DoE LBNL DoE BNL, FNAL, LBNL, Indiana University	9 5 1 1 3 6 7 18	2 1 1 2 1 1 1 1	4 1 2 1 2 1 2	1 2 1 1 1 2 2 3 3 3	1 1 1 1 1 1 1	1 1 1 1	1	
30 31 32 33 34 35 36 37 38 39	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines Astronomy and Phys Catalina Real-Time Transient Survey (CRTS): a digital, panoramic, synoptic sky survey DOE Extreme Data from Cosmological Sky Survey and Simulations Large Survey Data for Cosmology Particle Physics: Analysis of LHC Large Hadron Collider Data: Discovery of Higgs particle Belle II High Energy Physics Experiment	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DOE LBNL sics Caltech DoE Argonne, University of Washington DoE LBNL DoE BNL, FNAL, LBNL, Indiana University DOE PNNL	9 5 1 1 3 6 7	2 1 1 2 1 1 1 1	4 1 2 1 2 1 2	1 2 1 1 1 2 2 3	1 1 1 1 1 1 1	1 1 1 1	1	
30 31 32 33 34 35 36 37 38 39 40	CINET: Cyberinfrastructure for Network (Graph) Science and Analytics NIST Information Access Division analytic technology performance measurement, evaluations, and standards The Ecosystem for Ress DataNet Federation Consortium DFC The 'Discinnet process', metadata <-> big data global experiment Semantic Graph-search on Scientific Chemical and Text-based Data Light source beamlines Astronomy and Phys Catalina Real-Time Transient Survey (CRTS): a digital, panoramic, synoptic sky survey DOE Extreme Data from Cosmological Sky Survey and Simulations Large Survey Data for Cosmology Particle Physics: Analysis of LHC Large Hadron Collider Data: Discovery of Higgs particle	Virginia Tech NIST earch UNC Chapel Hill Discinnet Labs NIST DOE LBNL sics Caltech DoE Argonne, University of Washington DoE LBNL DoE BNL, FNAL, LBNL, Indiana University DOE PNNL	9 5 1 1 3 6 7 18	2 1 1 2 1 1 1 3 1	4 1 2 1 2 1 2 3	1 2 1 1 1 2 2 3 3 3	1 1 1 1 1 1 1	1 1 1 1	1	

42	ENVRI, Common Operations of Environmental Research Infrastructure	Cardiff University	11	2	1	2	5	1	4	1
43	Radar Data Analysis for CReSIS Remote Sensing of Ice Sheets	Indiana University	19	3	2	3	2	2	1	1
44	4 UAVSAR Data Processing, Data Product Delivery, and Data NASA JPL		9	2	4	4	1		2	1
45	NASA LARC/GSFC iRODS Federation Testbed	NASA Langley	4	1	1	3	1			
46	MERRA Analytic Services MERRA/AS	NASA GSFC	5	4	1	3	1			2
47	Atmospheric Turbulence - Event Discovery and Predictive Analytics	NASA HQ	8	2	4	2	1		1	
48	Climate Studies using the Community Earth System Model at DOE's NERSC center	NCAR	7	3	1	1	2			1
49	DOE-BER Subsurface Biogeochemistry Scientific Focus Area	Doe LBNL	5	3		1	1			1
50	DOE-BER AmeriFlux and FLUXNET Networks	Doe LBNL	6	5	1	2	1			1
	Energy									
51	Consumption forecasting in Smart Grids	University of Southern California	7	2	1	1		1		1

The specific requirements are divided into 7 categories motivated by features in the NIST Big Data PWG reference architecture. The abbreviations used in Table 2 are spelt out in Table 3. This also gives total counts for each requirement type and average counts per use case. Note that summing bottom 7 rows of column 3 implies that the average total number of specific requirements per use case is 10.92

Specific Requirement Category	Abbreviation in Table 1	Count	Average per Use Case
Generic	G	439	8.61
Data Sources	S	121	2.37
Data Transformation	T	113	2.22
Capability Infrastructure	С	128	2.51
Data Consumer	U	62	1.22
Security & Privacy	Р	53	1.04
Lifecycle Management		57	1.12
Other	0	23	0.45

Table 3: Specific and Generic Requirements and their Number

3 Use Case Requirements

Our process for derivation of requirements extraction involved two steps. The first step is to extract specific requirements based on each application's characteristics, including detailed information on:

- Data sources (data size, file formats, rate of growth, at rest or in motion, etc.)
- Data transformation (data fusion, analytics)
- **Capability** infrastructure (software tools, platform tools, hardware resources such as storage and networking)
- Data Consumer (usage, processed results in text, table, visual, and other formats)
- Security & Privacy
- Lifecycle Management (curation, conversion, quality check, pre-analytic processing, etc.)
- with a final "Other" category which largely corresponds to mobile access requirements.

The second step is to aggregate each application's specific requirements into high-level generalized requirements that are vendor-neutral and technology-agnostic. Note that these use cases and requirements are not exhaustive.

The use case and requirements information is presented online at the following links:

- Index to all use cases [12]
- List of specific requirements versus use case [17]

- List of general requirements versus architecture component [18]
- List of general requirements versus architecture component with record of use cases giving requirements [19]
- List of architecture components and specific requirements plus use case constraining the components [20]

There were 35 generic requirements [18] summarizing 439 specific requirements from the 51 use cases. This implies that on average 12.54 specific requirements were summarized in each generic requirement and this corresponded to an average of 8.61 specific requirements per use case. This was a subset of the 557 total specific requirements or 10.92 per use case. Column 2 of Table 4 gives the number of specific requirements driving this generic requirement.

#	Count	Generic Requirement
Da	ita Source	e Requirements (DSR)
1	28	Needs to support reliable real time, asynchronous, streaming, and batch processing to collect data from centralized, distributed, and cloud data sources, sensors, or instruments.
2	22	Needs to support slow, bursty, and high-throughput data transmission between data sources and computing clusters.
3	28	Needs to support diversified data content ranging from structured and unstructured text, document, graph, web, geospatial, compressed, timed, spatial, multimedia, simulation, and instrumental data.
Tra	Insformati	ion Provider Requirements (TPR)
1	38	Needs to support diversified compute-intensive, analytic processing, and machine learning techniques.
2	7	Needs to support batch and real-time analytic processing.
3	15	Needs to support processing large diversified data content and modeling.
4	6	Needs to support processing data in motion (streaming, fetching new content, tracking, etc.).
C		Provider Requirements (CPR)
1	29	Needs to support legacy and advanced software packages (software).
2	17	Needs to support legacy and advanced computing platforms (platform).
3	23	Needs to support legacy and advanced distributed computing clusters, co-processors, input output (I/O) processing (infrastructure).
4	14	Needs to support elastic data transmission (networking).
5	35	Needs to support legacy, large, and advanced distributed data storage (storage).
6	13	Needs to support legacy and advanced executable programming: applications, tools, utilities, and libraries (software).
Da	ata Consu	imer Requirements (DCR)
1	4	Needs to support fast searches (~0.1 seconds) from processed data with high relevancy, accuracy, and high recall.
2	16	Needs to support diversified output file formats for visualization, rendering, and reporting.
3	2	Needs to support visual layout for results presentation.
4	11	Needs to support rich user interface for access using browser, visualization tools.
5	20	Needs to support high-resolution multi-dimension layer of data visualization.
6	1	Needs to support streaming results to clients.
Se	curity and	d Privacy Requirements (SPR)
1	32	Needs to protect and preserve security and privacy on sensitive data.
2	12	Needs to support multi-level policy-driven, sandbox, access control, authentication on protected data.
Life	ecycle Ma	anagement Requirements (LMR)
1	20	Needs to support data quality curation including pre-processing, data clustering, classification, reduction, format transformation.
2	2	Needs to support dynamic updates on data, user profiles, and links.
3	6	Needs to support data lifecycle and long-term preservation policy, including data provenance.
4	4	Needs to support data validation.
5	4	Needs to support human annotation for data validation.
6	3	Needs to support prevention of data loss or corruption.
7	1	Needs to support multi-site archival.
8	2	Needs to support persistent identifier and data traceability.
9	1	Needs to support standardizing, aggregating, and normalizing data from disparate sources.
0		irements (OR)
1	6	Needs to support rich user interface from mobile platforms to access processed results.
_		

Table 4: Generic Requirements with Count of Number of Motivating Specific Requirements

2	2	Needs to support performance monitoring on analytic processing from mobile platforms.
3	13	Needs to support rich visual content search and rendering from mobile platforms.
4	1	Needs to support mobile device data acquisition.
5	1	Needs to support security across mobile devices.

4 Conclusions

The use cases are exemplars, and there are several areas where additional coverage would be important. The NBD-PWG has produced the current V1.0 collection summarized in this paper to present a coherent description and send information to the other working groups. The current collection of use cases includes the topics of Table 2. The NBD-PWG plans to add categories and use cases to this collection. The recommendations in Section 3 were abstracted from the use cases. These recommendations need more study both within this working group, and with other working groups.

The use cases have already spawned other activities including backdrop for Big Data standards, patterns [7, 8] based on earlier work in parallel computing [21-23], benchmarks and software architectures [10, 11].

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