The Current State of Big Data Analysis

In this report we discuss the current state of big data, which is estimated to already exist in the exabyte range. We also examine trends in analysis platform technology, and look at changes in the analysis of big data that accompany the shift to real-time solutions.

3.1 The Current State of Big Data

The term “big data” has become a common word recently, but it is still very hard to paint a precise picture of what it is. The main reasons for this are the fact that the meaning of “big data” differs substantially depending on the standpoint or opinion of the speaker, and the fact that it can be effectively applied in a broad array of cases across a range of industries. In a 2013 survey conducted by the Ministry of Internal Affairs and Communications that attempted to provide a comprehensive understanding of the current state of big data, it was reported that the amount of big data traffic in Japan is increasing year by year.

Looking at the amount of traffic by media type, we can see that a high total volume of data is obtained from POS, RFID, and GPS, and over the years the amount of medical data (electronic health records, diagnostic imaging) and M2M data (GPS, RFID) has grown significantly. The survey states that data is generated in a variety of ways and covers a range of media types, and explains that data falls under three categories in different data formats (Figure 1).

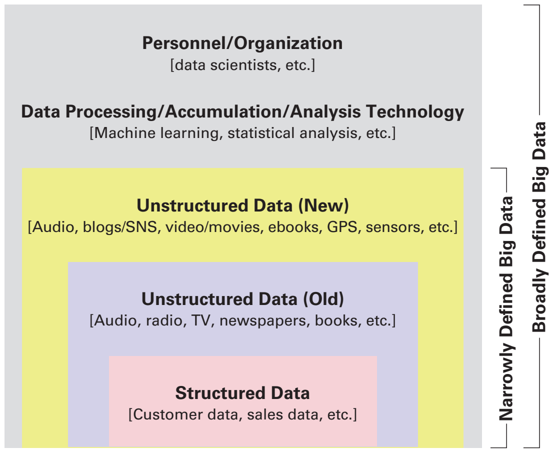
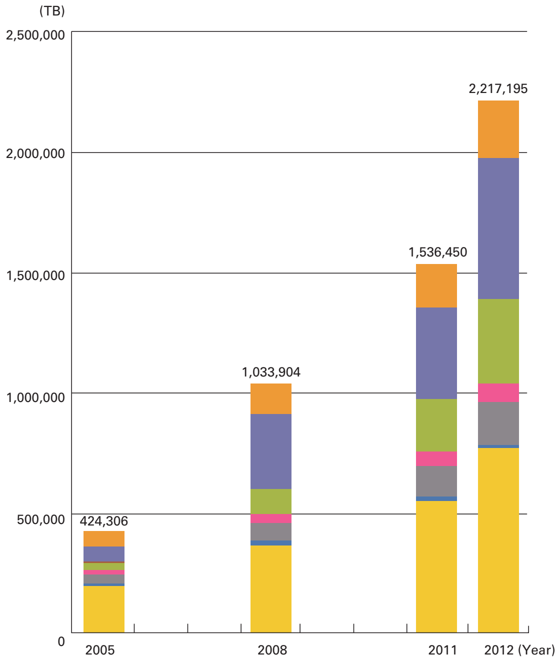


Figure 1: Three Types of Data in Different Formats



(Unit: TB)

	2005	2008	2011	2012 (Year)
Access logs	521	1,008	1,566	2,147
Blog and SNS posts	155	379	721	1,129
Email	64,566	121,085	178,501	238,048
Weather data	877	1,958	4,176	6,229
RFID data	64,519	309,559	370,440	583,942
GPS data	33,116	104,928	228,801	348,143
E-commerce sales logs	12	28	50	69
Mobile phones	17,765	36,068	56,544	75,881
Static IP phones	38,035	80,958	132,017	178,474
CTI audio log data	2,509	5,662	10,878	15,019
Image diagnosis	71	191	445	630
Electronic health records	227	636	1,032	1,635
Business logs	1	2	4	6
Electronic receipts	2	4	5	7
POS data	201,823	371,272	551,026	765,424
Accounting data	100	161	234	397
Customer databases	4	7	11	16
TOTAL	424,306	1,033,904	1,536,450	2,217,195

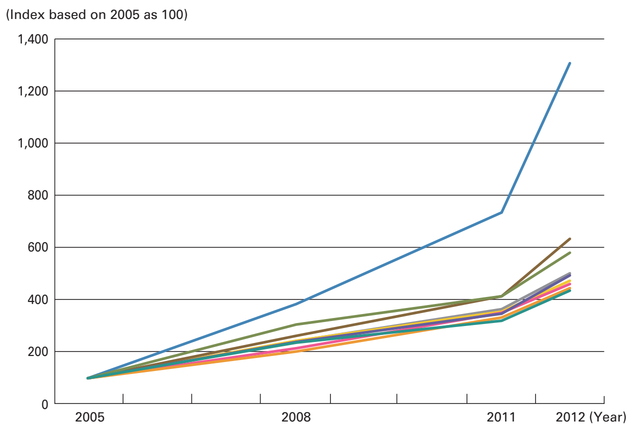
Figure 2: Big Data Traffic Estimates*1

*1 http://www.soumu.go.jp/johotsusintokei/whitepaper/ja/h25/html/nc113220.html (in Japanese)

However, from a data analysis perspective, the unstructured data (new) group includes data with standard formats specified such as POS, RFID, and GPS (in other words, structured data) in some cases. In other cases streamed data such as video, audio, and text includes metadata including the title or author. This suggests we should actually consider these examples as mixed data that includes both structured and unstructured data. Figure 2 indicates that big data traffic in Japan is dominated by structured data rather than unstructured data.

The figures below show estimated big data traffic by industry type (Figure 3) and accumulated volume (Figure 4), as reported in the Ministry of Internal Affairs and Communications survey.

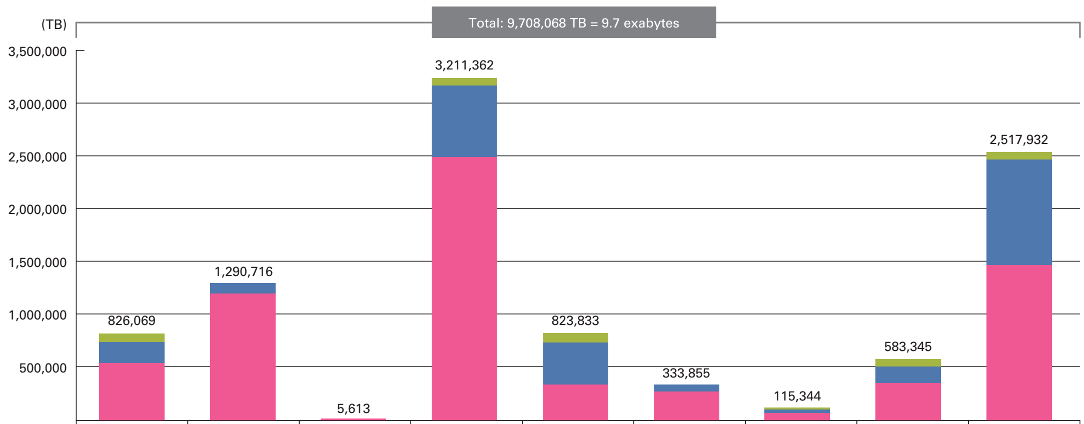
One thing of great interest regarding these estimates is that despite traffic amounts increasing with roughly the same characteristics (except for the real estate industry), accumulated amounts vary drastically for each industry. Assuming that the amount of big data accumulated shows the degree of utilization, it can also be surmised that this indicates a difference in commitment to initiatives for the application of big data in each industry. However, it may be that this just reflects that each



(Index based on 2005 as 100)

	2005	2008	2011	2012 (Year)
Manufacturing	100	233	320	431
Construction	100	303	411	576
Power/Gas/Water	100	200	327	436
Commerce	100	239	345	496
Finance/Insurance	100	211	349	459
Real estate	100	378	732	1,310
Transportation	100	260	410	632
Telecommunications	100	242	351	462
Service	100	236	363	499

Figure 3: Trends in Big Data Distribution Volume (By Industry)*²



	Manufacturing	Construction	Electricity gas and water supply	Commerce	Finance and insurance	Real estate	Transportation	Information and communicaitons	Services
Accumulation inside enterprises	543,156	1,194,956	3,722	2,468,219	334,843	270,270	76,887	350,485	1,455,067
Accumulation outside enterprises, inside Japan	203,562	90,900	1,376	678,545	412,397	63,237	30,258	167,949	990,394
Accumulation outside enterprises, outside Japan	79,350	4,860	515	64,598	76,594	348	8,199	64,911	72,472
Total	826,069	1,290,716	5,613	3,211,362	823,833	333,855	115,344	583,345	2,517,932

Figure 4: Big Data Accumulation Volume (By Industry, in 2012)*³

*2 http://www.soumu.go.jp/johotsusintokei/whitepaper/eng/WP2013/chapter-1.pdf#page=19
*3 http://www.soumu.go.jp/johotsusintokei/whitepaper/eng/WP2013/chapter-1.pdf#page=20

industry has different practices. Looking at the amount of accumulated data by industry, it is evident that B2C industries accumulate more data than B2B ones, and that most big data is kept private by its owners.

Given that exabytes of data is already in circulation according to the Ministry of Internal Affairs and Communications survey results, it is fair to say that the use and application of big data has started. However, it is becoming clear that the primary utilization of big data, namely to gain new knowledge by sorting and analyzing the big data collected and accumulated from vast data sources, is only now beginning to happen.

With regard to discussion of issues relevant to big data for promoting and accelerating its future utilization and application, two issues often raised are how to promote the sharing of big data, and how to obtain new knowledge through its analysis. In this context, three key words that are frequently encountered are M2M, IoT, and CPS. To briefly cover the definitions of each of these, Machine-to-Machine (M2M) is technology that enables communication between devices of the same type using wired or wireless communication systems, while the Internet of Things (IoT) involves uniquely identifiable objects represented virtually in an Internet-like structure. A Cyber-Physical System (CPS) is a system of cooperative computational elements that control physical entities. Rather than independent concepts, it may be best to think of these as presenting three perspectives on networks comprised of devices such as sensors. For example, package pickup and delivery management using RFID tags involves attaching an RFID tag to each package, and when a package passes near an RFID reader, data with location information added is generated. By collecting this data and tracing the location information for a particular package, it is possible to check the route that package has taken, and where it is currently stored. Furthermore, if you trace all the packages handled by the pickup and delivery management system, you can accurately ascertain the delivery centers where packages are concentrated. With the proliferation of smartphones these days, the activities of people can also be tracked using the same method. Collecting the data generated by each device creates big data, which it is believed would provide knowledge useful for work optimizations and marketing.

3.2 Technology Trends in Big Data Analysis Platforms: A Shift to Real-Time Solutions

The analysis of big data generated from device networks based on the M2M, IoT, and CPS concepts described earlier obviously demands immediacy. That means big data analysis platforms must accommodate the need for real-time analysis.

For many, platform technology for big data analysis calls to mind distributed processing platforms based on MapReduce, in particular. However, applying MapReduce architecture designed for batch processing to real-time analysis presents difficulties. Because the process results are not determined until a job finishes, a delay equal to the processing time occurs. One solution for reducing this time is to optimize and speed up the processing itself, but naturally there are limitations. Another measure is to reduce the size of batch processing, but when too small batch processing becomes meaningless. Normally, MapReduce jobs require anywhere between a few minutes to a few hours to process, and reducing this to the response time of a few seconds that is acceptable for web services is practically impossible.

Two approaches have been evaluated in research into real-time big data analysis platforms. The first involves responding to user requests in real time, and this covers cases in which response performance is improved by enhancing the functions of a MapReduce platform itself, as well as cases envisaged as platform systems that incorporate MapReduce, with MapReduce used internally, and improvements to response performance made in other areas. The other approach is to actually execute data processing in real time, using platform technology that implements so-called "real-time stream processing" in place of MapReduce.

MapReduce Online*4 is an example of enhancing the functions of the MapReduce platform itself. In this case, pipelines are used to handle the delivery of data between Map processes and Reduce processes with a heavily modified version of Hadoop. These enhancements enable users to check job status details during processing, in other words making event monitoring possible. It also allows stream processing to be written into MapReduce applications.

Examples of platform systems that incorporate MapReduce include the two open source clones that follow the idea of Google's Dremel*5: "Apache Drill*6" and "Cloudera Impala*7." Neither carry out data processing in real time, but they demonstrate equivalent low delay query response performance.

Apache Storm (Twitter Storm)*8 is an example of real-time stream processing. Storm was originally a system developed by BackType, which conducted Twitter analytics. After Twitter acquired BackType, Storm was made open source via the Apache Project, but it is a versatile big data processing platform.

Storm incorporates a stream engine that enables Complex Event Processing (CEP), ensuring that lossless data streams are supplied to the entities known as Spouts/Bolts that carry out big data processing. Storm stream flow is expressed in units called tuples, with overall stream processing implemented by defining topologies that connect Spouts and Bolts. Spouts are entities that represent data sources, and Bolts are entities that govern the conversion or processing of data. Their definitions and functions are completely different, but they could be thought of as Map and Reduce in MapReduce.

Like Hadoop, Storm can be comprised of clusters, and it operates four types of software: the Nimbus, Zookeepers, Supervisors, and Workers. The Nimbus is the master node that handles the scheduling and monitoring of Workers. Zookeepers are the distributed lock managers that are also used in Hadoop. Supervisors receive requests from the Nimbus and control the launch and termination of Workers. Workers function as the processes that carry out actual processing. Placing these pieces of software appropriately in nodes within a cluster achieves high scalability and fault-tolerance. Storm itself is written in a Lisp-like language called Clojure, and runs on a Java VM. Accordingly, Spouts and Bolts can be written using a variety of development languages that run on Java VMs, such as Java.

Here we have introduced the challenges of enabling real-time big data analysis platforms, as well as a number of examples, but it appears that more and more are seeing the appearance of Apache Storm as a trend towards a de facto standard for these platforms. It seems a simple programming model in common with Hadoop (MapReduce) and Twitter analytic performance are requirements expected of a versatile platform.

So, will Storm replace Hadoop as an open source big data analysis platform? The answer to this question seems likely to be that both will continue to become compartmentalized. This is because immediacy is not required for all big data analysis. As mentioned, those demanding big data analysis with a real-time response will transition to Storm, but those for which conventional batch processing is sufficient (or necessary) will probably continue to use Hadoop. Hybrid system architecture methods that utilize Storm for the preprocessing of Hadoop analysis (data shaping, filtering, and matching), or combine batch processing with stream processing in what is known as Lambda architecture, have also been proposed. Currently, it is generally accepted that both are mutually complementary.

*4 http://db.cs.berkeley.edu/papers/nsdi10-hop.pdf
*5 http://research.google.com/pubs/pub36632.html
*6 http://incubator.apache.org/drill/
*7 http://blog.cloudera.com/blog/2012/10/cloudera-impala-real-time-queries-in-apache-hadoop-for-real/
*8 http://storm.incubator.apache.org/

3.3 Changes in Big Data Analysis Due to the Shift to Real-Time Solutions

The shift towards real-time big data analysis platforms is understood to be a response to improve velocity, which is one of the often-quoted "3Vs" that define big data (Volume, Variety, and Velocity). According to Gartner, which coined the 3Vs definition, velocity is the speed of data creation and processing. For example, the analysis of sensor and log data, the analysis of spatiotemporal data using GPS information, and the analysis of stream data obtainable from social media are all specific examples in which this velocity requirement must be met. For existing analysis cases such as these, there are well-known examples of obtaining new knowledge from previously accumulated data, including records of abnormal behavior detection and spatial migration, as well as sentiment analysis. However, due to improvements in the immediacy of real-time big data analysis platforms, in the future it is thought that analysis methods will become more diverse, such as time-series analysis that places more emphasis on timelines, and estimates based on this.

3.3.1 Wikipedia as Social Big Data

We are trying out trend analysis using Wikipedia Pageview Count (Wikipedia PVC: http://www.gryfon.iij-ii.co.jp/ranking/) (in Japanese) as an example of analysis focused on the timeline of big data. As everyone knows, Wikipedia is the most successful Internet encyclopedia. It has adopted an extremely open administration policy, and because its databases can be obtained charge-free, it is utilized for research and a variety of other purposes. The Wikipedia PVC is part of the information published, and has been available since around January 2013. It indicates the number of page views for each Wikipedia page over the last hour, with updates posted every hour or two. By combining Wikipedia PVC and the Wikipedia database, they are usable as time-series data for indicating social trends, and this can be considered as an example of social big data obtainable via the Internet. Because it has the properties of an encyclopedia, the following characteristics apply compared to typical social media sites (SNS or blogs).

- Users are allowed to make alterations themselves, but because there are measures in place to prevent venting through article content using guidelines, etc., it is possible to find common denominators regarding society as a whole.
- Because it is an encyclopedia, the content is very thorough, with linked data formed within a close space.
- The service has high public recognition, and users use it to learn the details of topics they don't know about, and discover related information.
- It supports many languages, and in many cases each page is clearly mapped out for each language.

When performing text analysis using messages obtained from general social media for trend analysis, etc., the lack of consistent terminology can hinder data analysis. However, this is less likely to be a problem with Wikipedia data that keeps meaning-related outbursts in check, and as a result we believe that analysis results that are easily understandable by people can be obtained.

3.3.2 Analysis of Wikipedia PVC Time-Series Fluctuations

For Wikipedia, which is well-known as an encyclopedia, the dominant usage pattern likely involves users finding the page they want by searching for the topic they are interested in from the main page or a search engine.

By focusing on a certain Wikipedia page, and observing the time-series fluctuations in its PVC, we can confirm that a peak is reached at some point, after which activity gradually subsides. In particular, after investigating a number of pages with notable peaks further, we learned that pages dealing with topics reported on TV broadcasts or Internet news showed large responses. In other words, this supports the hypothesis that viewers of TV programs and readers of Internet news look up topics they don't know about on Wikipedia when they arise.

To verify this hypothesis, we focused on serial dramas, surveying the relationship between each broadcast time and time-series fluctuations in the Wikipedia PVC. We concentrated on serial dramas because we had confirmed it was highly likely for the PVC peak for the Wikipedia page to occur at the same time as each episode was broadcast. Television dramas also have viewer ratings, a widely-known index of viewer numbers, and it was important to investigate the relationship between this and the Wikipedia PVC.

Wikipedia PVC provides data on all 334 serial dramas broadcast on commercial stations since 2008. Of these, we used the following method to analyze 244 dramas with complete sets of Wikipedia PVC data.

1. Assuming a broadcast time of one hour for each drama episode, we extracted a single set of time-series data for the 168 hours between the broadcast time and an hour before the next broadcast.
2. We performed regression analysis on the extracted time-series data, and used the coefficient obtained as the social interest level of that episode.
3. We investigated the correlation between the social interest level and average viewer ratings for each episode, and confirmed the significance of this.

For the regression analysis in step two, we used the regression formula $pvc = \alpha * \exp(\beta * t) + \gamma$, based on knowledge in econometrics that “social events fluctuate exponentially.” We also adjusted peak values to take into consideration broadcast time delays or expansion.

Non-linear regression analysis results indicate a high peak during broadcast times in each case, which subsequently converges with the γ value. After looking into the correlation between the coefficients α, β, and γ obtained from analysis and average viewer ratings, correlation was seen with the Y value. Figure 5 shows the correlation analysis results between the γ value for each episode of the TV drama Hanzawa Naoki, and its average viewer ratings.

At the time of writing, we had analyzed the correlation between the γ value and average viewer ratings for 40 of 244 sets of valid data, and results showed significant correlation. We will analyze correlation for the remaining 204 cases, but because we have found cases in which Wikipedia PVC fluctuations and viewer behavior did not match, particularly for dramas with low viewer ratings, we plan to clarify the number of cases in which significant valid data can be confirmed, as well as the range of Wikipedia PVC values for which this analysis method can be applied.

3.4 Summary

In this report, we examined the current state of big data through the lens of the key words M2M, IoT, and CPS. We also looked at technological trends related to analysis platforms that demand a shift to real-time solutions, and the diversification of big data analysis techniques for which knowledge can be obtained from time-series data.

We imagine that attempts to obtain detailed data live and utilize it in processing platforms with high immediacy to identify what is happening right at this moment will make it possible to obtain dynamic, micro-knowledge vastly different from big data analysis that obtains conventional static macro-knowledge. This new knowledge may even contain signs of what is yet to come. Finding these signs before anyone else could be the challenge for big data in the future.

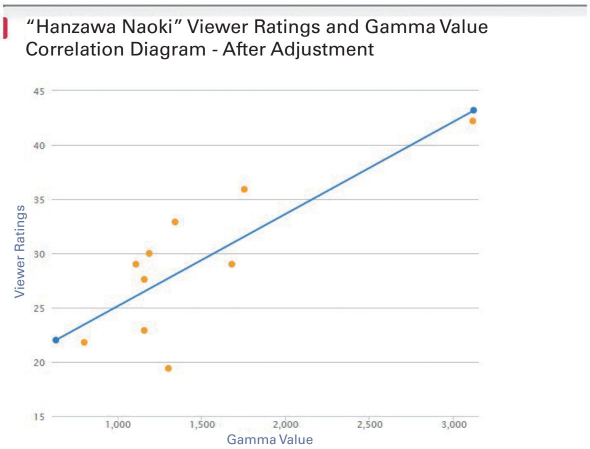


Figure 5: Correlation Analysis Results for γ Value and Viewer Ratings of Each “Hanzawa Naoki” Episode

Author:

Akito Fujita

Chief Architect, Business Strategy and Development Center, IIJ Innovation Institute Inc. (IIJ-II). Mr. Fujita joined IIJ in 2008. He is engaged in the research and development of cloud computing technology utilizing knowledge gained through structured overlay research.