Big Data Management System: A Computer View

Yao Wu
Key Laboratory of Data Engineering and Knowledge Engineering of Ministry of Education, Beijing, China
School of Information, Renmin University of China, Beijing, China
Email: ideamaxwu@ruc.edu.cn

***Abstract*—Big data is emerging and rumors go around. Big data is being generated by everything around us at all times. Big data is changing the way people work, live and leisure. Big data is a term for data sets that are so large or complex that traditional data processing applications are inadequate. Challenges include analysis, capture, data curation, search, sharing, storage, transfer, visualization, querying and information privacy. In this paper, we put our effort in the big data management system. We propose datar, a new prospective of BDMS from the point the architecture leveraging ideas from computer. We introduce the five key components of datar by reviewing the the current status of big data management system. We also present evaluation and application of datar and conclude with future directions. In this paper, we review researches on BDMS and discuss open peoblems and give poteantial frontier by examing its sysmatic architecture as datar.**

I. Introduction

A. From Computer to Datar

During the last several decades, data management principles such as physical and logical independence, declarative querying and cost-based optimization have led to a multi-billion dollar industry. More importantly, these technical advances have enabled the first round of business intelligence applications and laid the foundation for managing and analyzing Big Data today. The many novel challenges and opportunities associated with Big Data necessitate rethinking many aspects of these data management platforms, while retaining other desirable aspects.

As Turing proposed the question "Can machines think?" [1], the imitation game begins. However, before that, Von Neumann had started the engineer research on computer and described the logical design of a computer using the stored-program concept in 1945, which has controversially come to be known as the von Neumann architecture [2]. More ago, English mathematician and computer pioneer Charles Babbage proposed the Analytical Engine, a mechanical general-purpose computer designed. The goal of the pioneers is to design a computing machine better than human brain, which can liberate the tedious computing from manual work.

The practice [3] and theory [4] contribution of Bachman and Codd open up the research on database. And the steps never stop, Ingres [5], Postgres [6], Mariposa [7], C-Store [8] and VoltDB [9].

From the computer to datar, we never stop liberating human from tedious and complex work. Although BDMS is a complex set of functionality, we think is as an amplified datar. In point of this view, we summarise and describe the main components in big data management system, to provide a full understanding for beginners and experts.

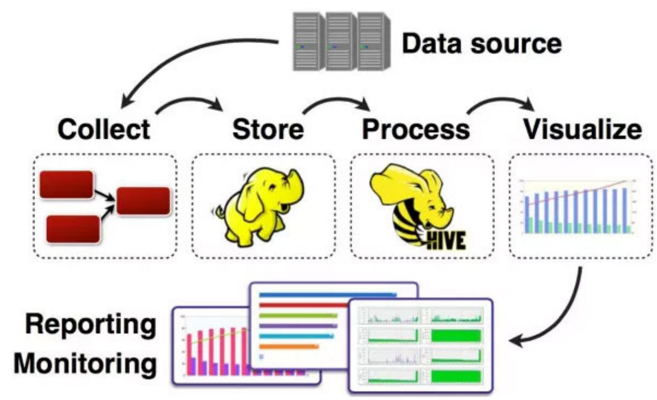

Fig. 1. A typical workflow for big data.

As shown in Fig. 1, BDMS consists of several core components such as, collect, store, process and visualize. Compared with traditional DB systems, BDMS architecture is more flexible and open due to various focus-ons. In this paper, we unify the BDMS as **datar**, a proposed general architecture to design and build BDMS, with respect to the term **computer**.

As we all knnow, the popular computer structure is divided into five parts, input, storage, compute, control and output, in which, computation is the center. If you look closely, you will find that, the BDMS is just the same as computer, consisting of input (data feed), storage, compute (data analysis), control (transaction) and output (visualization), in which, storage is the center. In other words, we can call a computer Fast Computation Processing System (FCPS). Likewise, the BDMS is called as datar, a big data management system centered at data. To better explain the similarity and differences between a computer and a datar, in terms of architectuer, we use Fig. 2 to illustrate.

B. What is Datar

Definition (Datar) *A datar is a stack of coherent softewares with specific functionality that can be applied to mine valuable information from persisted data automatically, where specific functionality refer to input, storage, compute, control and output of the big data.* AsterixDB [10] with its extensions can be an materilization of envisioned datar.

A datar, i.e., full-function BDMS, consists of five parts, data feed, data storage, data analysis, data transaction and data visualization. Compared to the computation-centered computer, a datar is data-centered. We take AsterixDB for example, which is a new, full-function BDMS. Data feed is how the data gets into the system. In AsterixDB, data feeds are a built-in mechanism allowing new data to be continuously ingested into system from external sources, incrementally populating the datasets and their associated indexes [11]. Data storage is how the data stored in the system and how the index are built. In AstrixDB, data and index are stored based on LSM structure [12]. Data analysis is how to mine valuable information from stored data. A bunch of methods are applied. Besides, the excution of data processing is also part of data analysis, like Hyracks [13] in AsterixDB. Data reansaction is how to control data when it is processed. It is different from the traditional DB systems which have strict ACID. Another very important aspect of datar is visualization. Cloudberry [1] is a research prototype to support interactive analytics and visualization of large amounts of spatial-temporal data.

C. How Far Datar Can Go

In the late 1970s, the concept of “database machine” emerged, which is a technology specially used for storing and analyzing data. With the increase of data volume, the storage and processing capacity of a single mainframe computer system became inadequate. In the 1980s, people proposed “share nothing”, a parallel database system, to meet the demand of the increasing data volume. The share nothing system architecture is based on the use of cluster and every machine has its own processor, storage, and disk. In the late 1990s, the advantages of parallel database was widely recognized in the database field.

However, many challenges on big data arose. With the development of Internet servies, indexes and queried con- tents were rapidly growing. Therefore, search engine companies had to face the challenges of handling such big data. Google created GFS and MapReduce programing models to cope with the challenges brought about by data management and analysis at the Internet scale. In January 2007, Jim Gray, a pioneer of database software, called such transformation “The Fourth Paradigm”. He also thought the only way to cope with such paradigm was to develop a new generation of computing tools to manage, visualize, and analyze massive data.

Over the past few years, nearly all major companies, including EMC, Oracle, IBM, Microsoft, Google, Amazon, and Facebook, etc. have started their big data projects. Big data shows great value in real application and challenges arise. At present, data has become an important production factor that could be comparable to material assets and human capital. Some literature discuss obstacles in the development of big data applications, such as data representation, data reduction and compression and data life cycle management.

In this paper, we describe the Big Data Management System(BDMS) from a new perspective: the view of a computer. We focus our attention on the system architecture in the BDMS and break it down into several parts to elaborate. Key techniques will be explained to better present the systematic functionality.

The paper is organized as follows. From section II to section VI, we introduce the BDMS from five aspects, input, storage, control, computation and output. Section VII provide a thourough evaluation on popular BDMS. Application of BDMS is given in Section VIII. Section IX follows with furute directions. Finally, we conclude with futures in section X.

[1] http://cloudberry.ics.uci.edu/

II. Data Input

A. Data Generation

1) Web Data: The size of the web is very huge and rapidly increasing. There is a lot of unstructured data from the web. he web pages do not have unifying structure. They are very complex as compared to traditional text document. Web data also includes social network data, location based service data and the linked pages.

Every second, approximately 6,000 tweets are tweeted; more than 40,000 Google queries are searched; and more than 2 million emails are sent, according to Internet Live Stats, a website of the international Real Time Statistics Project. But these statistics only hint at the size of the Web. As of September 2014, there were 1 billion websites on the Internet, a number that fluctuates by the minute as sites go defunct and others are born. And beneath this constantly changing (but sort of quantifiable) Internet that’s familiar to most people lies the ”Deep Web,” which includes things Google and other search engines don’t index. The Indexed Web contains at least 4.82 billion pages (Tuesday, 01 November, 2016).

2) Enterprise Data: The internal data of enterprises are the main sources of big data. The internal data of enterprises mainly consists of online trading data and online analysis data, most of which are historically static data and are managed by traditional ralation DBMSs in a structured manner. In addition, production data, inventory data, sales data, and financial data, etc., also constitute enterprise internal data, which aims to capture informationized and data-driven activities in enterprises, so as to record all activities of enterprises in the form of internal data.For examle, Amazon processes millions of terminal operations and more than 500,000 queries from third-party sellers per day. Walmart processes one million customer trades per hour and such trading data are imported into a database with a capacity of over 2.5PB.

3) Government Data: During the last decade, government agencies have collected various data sets, the more the merrier. Inundated with database schemas, documents, emails, web content and XML, agencies are left with daunting integration challenges.

Open government data is important because the more accessible, discoverable, and usable data is, the more impact it can have. These impacts include, but are not limited to: cost savings, efficiency, fuel for business, improved civic services, informed policy, performance planning, research and scientific discoveries, transparency and accountability, and increased public participation in the democratic dialogue.

4) Other Data: As scientific applications are increasing, the scale of datasets is gradually expanding, and the development of some disciplines greatly relies on the analysis of masses of data. In addition, pervasive sensing and computing among nature, commercial and social environments are generating heterogeneous data with unprecedented complexity. These datasets have their unique data characteristics in scale,

(a) Computer Architecture

(b) Datar Architecture

Fig. 2. Computer VS Datar comparison of architecture.

time dimension, and data category. According to the application environment and requirements, such datasets into different categories, so as to select the proper and feasible solutions for big data.

B. Data Feed

Data feed is also known as data acquisition,having continous data arrive into DBMS from external sources and incrementally populate a persisted dataset and associated indexes. In the past, ETL (Extract Transform Load) systems work the same way. It is also similar to stream data processing.

Extraction involves connecting source systems, selecting, collecting, analyzing, and processing necessary data. Transformation is the execution of a series of rules to transform the extracted data into standard formats. Loading means importing extracted and transformed data into the target storage infrastructure.

A simple way of having data being put into a Big Data management system on a continuous basis is to have a single program fetch data from an external data source, parse the data, and then invoke an insert statement per record or batch of records. It is hard to reason about the data consistency, scalability and fault-tolerance offered by an assembly 'gluing' together different systems. Therefore, it is natural for a BDMS to provide "native" support for data feed management.

In AsterixDB, we build a fault-tolerant data feed facility that scales through partitioned parallelism by using a high-level language. A generic plug-and-play model can help datar cater to a wide variaty of data sources and applications.

III. Data Storage

A. Data Storage

Big data storage refers to the storage and management of large-scale datasets while achieving reliability and availability of data accessing. We will review important issues including massive storage systems, distributed storage systems, and big data storage mechanisms. Various storage systems emerge to meet the demands of massive data. There are three main NoSQL databases technologies: key-value DB, column-oriented DB and document-oriented DB.

1) Key-Value DB: Dynamo[2] [14] by Amazon,Voldemort[3] [15] by LinkedIn and Redis[4] [16], Memcache DB[5] [17], Scalaris[6] [18], Riak, Tokyo Canbinet, Tokyo Tyrant.

Key-value Databases are constituted by a simple data model and data is stored corresponding to key-values. Every key is unique and customers may input queried values according to the keys. Such databases feature a simple structure and the modern key-value databases are characterized with high expandability and shorter query response time than those of relational databases.

Amazon **DynamoDB** is a fast and flexible NoSQL database service for all applications that need consistent, single-digit millisecond latency at any scale. It is a fully managed cloud database and supports both document and key-value store models. Its flexible data model and reliable performance make it a great fit for mobile, web, gaming, ad tech, IoT, and many other applications.

Voldemort is a distributed data store that is designed as a key-value store used by LinkedIn for high-scalability storage. It is neither an object database, nor a relational database. It does not try to satisfy arbitrary relations and the ACID properties, but rather is a big, distributed, fault-tolerant, persistent hash table.

Redis is an open source, in-memory data structure store, used as database, cache and message broker. **MemcacheDB** is a distributed key-value storage system designed for persistent. **Scalaris** is a scalable, transactional, distributed key-value store.

[2]https://aws.amazon.com/dynamodb/

[3]http://www.project-voldemort.com/

[4]http://redis.io/

[5]http://memcachedb.org/

[6]http://scalaris.zib.de/

Key-Value	Column	Document	Graph	Other
Dynamo	BigTable	MongoDB	Giraph	
Voldemort	Cassandra	SimpleDB	Neo4j	
Redis	Hbase	CouchDB	OrientDB	
MemcacheDB	HyperTable			
Scalaris				

TABLE I. POPULAR BIG DATA STORAGE SYSTEM.

It was the first NoSQL database, that supported the ACID properties for multi-key transactions.

2) Column-oriented DB: BigTable[7] [19] by Google, Cassandra[8] [20] by Facebook, Hbase[9] [21] cloned from BigTable, HyperTable[10].

The column-oriented databases store and process data according to columns other than rows. Both columns and rows are segmented in multiple nodes to realize expandability.

Bigtable is designed to handle massive workloads at consistent low latency and high throughput, so it's a great choice for both operational and analytical applications, including IoT, user analytics, and financial data analysis.

Cassandra is a free and open-source distributed database management system designed to handle large amounts of data across many commodity servers, providing high availability with no single point of failure.

3) Documnet-oriented DB: MongoDB[11] [22] open-source, SimpleDB[12] by Amazon, CouchDB[13] [23] by Apache.

Compared with key-value storage, document storage can support more complex data forms. Since documents do not follow strict modes, there is no need to conductmode migration.

MongoDB is a free and open-source cross-platform document-oriented database program. MongoDB uses JSON-like documents with schemas.

CouchDB is open source database software that focuses on ease of use and having an architecture that completely embraces the Web.

4) Graph-oreinted DB: Apache Giraph[14], Neo4J[15], OrientDB[16].

A graph database is a database that uses graph structures for semantic queries with nodes, edges and properties to represent and store data.

Neo4j is a graph database management system, an ACID-compliant transactional database with native graph storage and processing.

In addition, other companies and researchers also have their solutions to meet the different demands for storage of big

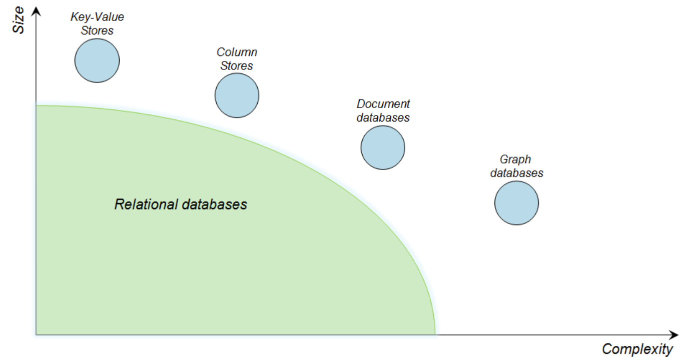

Fig. 3. Comparision of data storage model.

data. A lot of features include Pluggable Storage Engines (e.g., MySQL) provided by Voldemort. TiDB also supports external database connection. In this situation, storage is just like disk that can be added, replaced and deleted.

B. Data Index

Index is always an effective method to reduce the expense of disk reading and writing, and improve insertion, deletion, modification, and query speeds in both traditional relational databases that manage structured data, and other technologies that manage semistructured and unstructured data. However, index has a disadvantage that it has the additional cost for storing index files which should be maintained dynamically when data is updated.

Basic structures include Hash table, Tree-based index, Multidimensional index, and Bitmap index. Big data index has additional requirements, such as parallelisim, easily partitioned into pieces for parallel processing.

Artificial Intelligence indexing approaches are so called because of their ability to detect unknown behavior in Big Data. They establish relationships between data items by observing patterns and categorizing items or objects with similar traits. Latent Semantic Indexing and Hidden Markov Model are two popular AI indexing approaches. In Non-AI indexing approach, the formation of indexes does not depend on the meaning of the data item or the relationship between texts. Rather, indexes are formed based on items most queried or searched for in a particular data set.

IV. DATA COMPUTATION

A. Data Query

MapReduce [24], Dryad[17] [25], All-Pairs, Pregel [26], Spark[18] [27] are the popular programming models and excution engines. Many in-memory database are proposed to accellarate the computation.

MapReduce is a programming model and an associated implementation for processing and generating large data sets with a parallel, distributed algorithm on a cluster. The Dryad Project is investigating programming models for writing parallel and distributed programs to scale from a small cluster

[7]https://cloud.google.com/bigtable/
[8]http://cassandra.apache.org/
[9]http://hbase.apache.org/
[10]http://www.hypertable.org/
[11]https://www.mongodb.com/
[12]https://aws.amazon.com/simpledb/
[13]http://couchdb.apache.org/
[14]http://giraph.apache.org/
[15]https://neo4j.com/
[16]http://orientdb.com/
[17]https://www.microsoft.com/research/project/dryad/
[18]http://spark.apache.org/

to a large data-center. Pregel is Googles scalable and fault-tolerant platform with an API that is sufficiently flexible to express arbitrary graph algorithms. Apache Spark is a fast and general engine for big data processing, with built-in modules for streaming, SQL, machine learning and graph processing.

B. Data Analysis

The analysis can be from simple statistic to deep data mining technology. Nowadays, deep learnig has become a trend in analysis of big data. MLlib[19] [28] by Java, Scipy,Theano,Caffe[20] [29] by Python, TensorFlow[21] [30] by C++, Torch.

MLlib is Spark's machine learning library, focusing on learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction, as well as underlying optimization primitives. Caffe is a deep learning framework made with expression, speed, and modularity in mind. TensorFlow is an open source software library for machine learning in various kinds of perceptual and language understanding tasks.

V. Data Control

According to CAP theorem, it is not feasile for BDMS to fullfil ACID (Atomic Consistent Isolation Durable) from traditional DB. However, BASE (Basic Availability Soft-state Eventual consistency) is an alternative.CAP theorem says ot is impossible for a protocol to guarantee both consistency and availability in a partition prone distributed system. Most of the NoSQL database system architectures favour one factor over the other.

BigTable, used by Google App engine, and HBase, which runs over Hadoop, claim to be strongly consistent within a data-center and highly available meaning there's an eventual consistency between data-centers. Updates are propagated to all replicas asynchronously. Amazon's Dynamo, Cassandra and Riak instead sacrifice consistency in favor of availability and partition tolerance. They achieve a weaker form of consistency known as eventual consistency updates are propagated to all replicas asynchronously, without guarantees on the order of updates across replicas and when they will be applied.

A. Data Transaction

In databases, a transaction is a set of separate actions that must all be completely processed, or none processed at all. In partitioned databases, trading some consistency for availability can lead to dramatic improvements in scalability. It is hard to leverage between the speed and scale of NoSQL, and the relational, transactional strength and consistency of traditional RDBMS.

NewSQL [31] is next-generation scalable relational database management systems (RDBMS) for Online Transaction Processing (OLTP) that provide scalable performance of NoSQL systems for read-write workloads, as well as maintaining the ACID (Atomicity, Consistency, Isolation, Durability) guarantees of a traditional database system. One of the famous NewSQL is Google Spanner [32], which is a globally distributed NewSQL database.

[19]http://spark.apache.org/mllib/
[20]http://caffe.berkeleyvision.org/
[21]https://www.tensorflow.org/

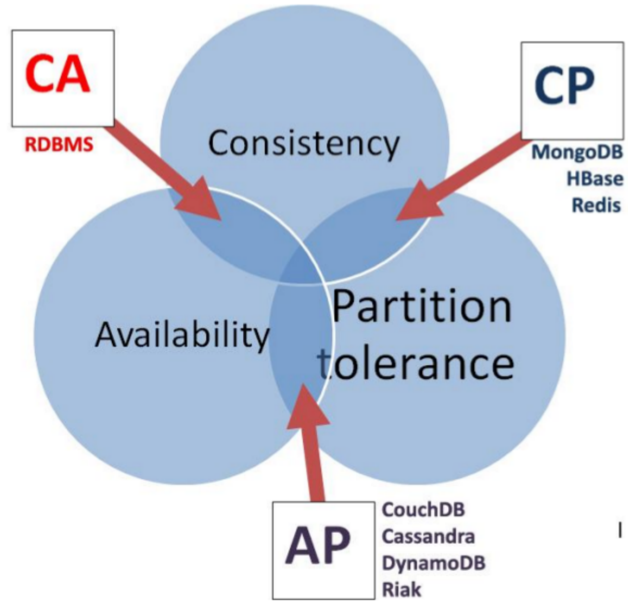

Fig. 4. CAP theorem with associated NoSQL DBs.

Item	DB	NoSQL	NewSQL
SQL	surpported	non-surpported	surpported
OLTP	not fully supported	supported	fully supported
Trans	ACID	CAP based BASE	ACID

TABLE II. Transaction comparision of DB, NoSQL and NewSQL.

NuoDB[22] that is a distributed database designed with SQL service: all the properties of ACID transactions, standard SQL language support and relational logic. ClustrixDB[23] is a distributed SQL database built for large-scale and fast-growing applications. VoltDB [9] is an insanely fast in-memory database with incredible high read and write speeds. CouchDB read operations use a Multi-Version Concurrency Control (MVCC) model.

Although NewSQL systems vary greatly in their internal architectures, the two distinguishing features common amongst them is that they all support the relational data model and use SQL as their primary interface

B. Data Recovery

Big data applications as well as operational systems must be supported by a robust and rapid recovery process. As database architecture has fundamentally changed to meet new application requirements, data protection needs to be redefined and re-architected as well.

Big data shook up the database arena, ushering in a new class of "scale out" technologies.The scale-out nature of the architecture can also be difficult for traditional backup applications to handle. Organizations that are deploying big data platforms and applications must realize the importance

[22]http://www.nuodb.com/
[23]http://www.clustrix.com/

of backing up their data. Platform-provided mechanisms such as replicas and snapshots are not sufficient to ensure proper data protection and to minimize downtime. Proper backup and recovery requires some investment but is well worth it given the role big data plays in driving business value. Some of the most common mechanisms[24] include:

- Multiple replicas of data eliminates the need for separate backup/recovery tools of big data.
- Lost data can be quickly and easily rebuilt from the original raw data.
- Backing up a petabyte of big data is not economical or practical.
- Remote disaster recovery copies can serve as a backup copy.
- Writing backup/recovery scripts for big data is easy.
- Big Data Backup/Recovery operations costs are very small.
- Snapshots are an effective backup mechanism for big data.

C. Resource Management

Big data computation always runs on thousands of machines, which needs the resource management among clusters. Mesos [33] is a platform for sharing commodity clusters between multiple diverse cluster computing frameworks. The fundamental idea of Hadoop YARN [34] is to split up the functionalities of resource management and job scheduling/monitoring into separate daemons.

VI. Data Output

A. Data Visualization

Visualization helps us take deep look into the big data, which provides us a interactive and graphic way to embrase the inside of big data. Tools like Tableau[25], Plotly[26], Visual.ly[27] are emerging.

Big Data analytics plays a key role through reducing the data size and complexity in Big Data applications. Visualization is an important approach to helping Big Data get a complete view of data and discover data values. Big Data analytics and visualization should be integrated seamlessly so that they work best in Big Data applications. Many conventional data visualization methods are often used, such as table, histogram, scatter plot, time line, data flow diagram, and entity relationship diagram, etc. Visualizations are not only static; they can be interactive. Interactive visualization can be performed through approaches such as zooming. Scalability and dynamics are two major challenges in visual analytics [35]. Visualization of big data with diversity and heterogeneity (structured, semi-structured, and unstructured) is a big problem.Big data visualization can be performed through a number of approaches such as more than one view per representation display, dynamical changes in number of factors, and filtering.

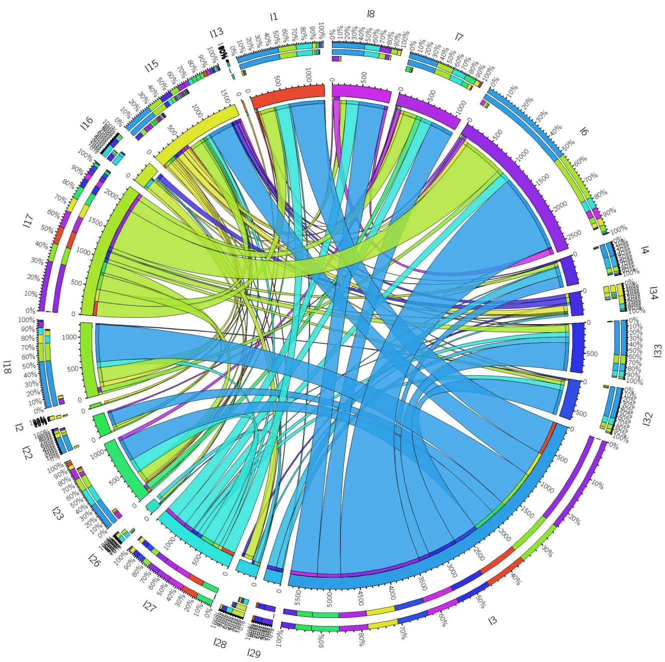

Fig. 5. Big data visualization.

System	Input	Storage	Compute	Control	Output
AsterxDB					
HBase					
Spark					

TABLE III. Comparision of popular systems components.

B. Data Sharing

Because sharing data [36] will necessarily increase the potential benefit to society of the subject's participation by providing greater opportunities for scientific discovery, Brakewood and Poldrack argued that researchers may have an ethical duty to share their data unless doing so would increase risk to the subjects.

In research filed, many insititutions share their data to promote the research. Governments also start share data to public for common benefits. However, some data like personal data and enterprise internal data cannot share since its privacy and confidetial. Therefore, some guidelines our regulations should be made to lead us properly share data, rather than share all or share nothing.

VII. Evaluation

Given different components of BDMS datar, some evaluation on representative systems can be found [37]. More work can be found about the performance evaluation on different aspects, i.e., scalability and efficiency. A monthly updated popularity ranking can be found at DB-Engines [28]

[24] http://www.networkworld.com/article/3113036/big-data-business-intelligence/debunking-the-most-common-big-data-backup-and-recovery-myths.html
[25] http://www.tableau.com/
[26] https://plot.ly/
[27] http://visual.ly/
[28] http://db-engines.com/en/ranking

System	Scale	Efficiency	Privacy	Heterity	Human
AsterxDB					
HBase					
Spark					

TABLE IV. COMPARISION OF SYSTEMS FUNCTIONALITY.

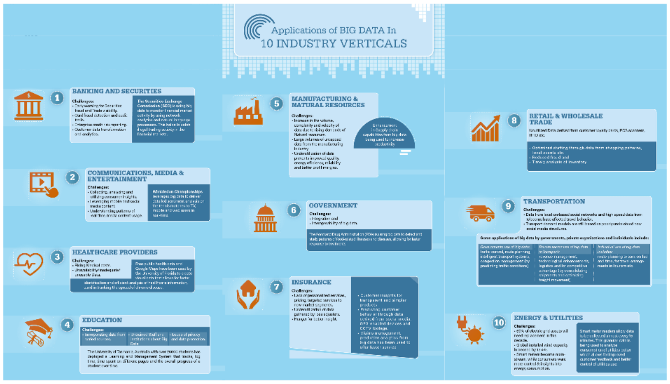

Fig. 6. Application of big data.

VIII. APPLICATION

Big data has been proposed as an advanced technolgy to solve large-scale and complex problems. Data driven applications have emerged in the past decade, such as structural data analysis, text analysis, web data analysis, multimedia data analysis and network analysis.

BAD [38] is an extended AsterixDB application that can continuously and reliably capture Big Data to enable timely and automatic delivery of new information to a large pool of interested users as well as supporting analyses of historical information. Currently, AsterixDB shows weak in temrs of deep computing of data.

More applications such as, IoT, Ad Tech and Gaming.

IX. FUTURE

Big data is confronted with many challenges, but the current research is still in early stage. Considerable research efforts are needed to improve the overall funcationability of big data.

A. Functionbility

Although we propose the five key parts as the core components of datar, it is still worthy of digging deep to fulfill the functionality of BDMS. Apache kafka[29] is a fast, scalable, durable, and fault-tolerant publish-subscribe messaging system.

B. Privacy and Security

The analysis capacity of big data may lead to privacy mining from seemingly simple information. Therefore, privacy protection will become a new and challenging problem.

[29] https://kafka.apache.org/

The safety of big data has drawn great attention of researchers. However, there is only limited research on the representation of multi-source heterogeneous big data, measurement and semantic comprehension methods, modeling theories and computing models, distributed storage of energy efficiency optimization, and processed hardware and software system architectures, etc. Particularly, big data security, including credibility, backup and recovery, completeness maintenance, and security should be further investigated.

C. Heterogeneity

The increasingly growing data cause a problem of how to store and manage such huge heterogeneous datasets with moderate requirements on hardware and software infrastructure. Many datasets have certain levels of heterogeneity in type, structure, semantics, organization, granularity, and accessibility.

D. Human Collaboration

Crowdsourcing, a new approach for problem solving, takes a large number of general users as the foundation and distributes tasks in a free and voluntary manner. In the big data era, crowdsourcing becomes a hot topic, which can amend the lack of human intelligence in the process of data analysis.

CrowdDB [39] is a good example to leverage human power into DB system.

E. Access Control

Amazon DynamoDB integrates with AWS Identity and Access Management (IAM) for fine-grained access control for users within your organization. You can assign unique security credentials to each user and control each user's access to services and resources. Access control is necessary for cloud-based database.

F. Data Redundancy and compression

Big data is highly reduntant. Redundancy reduction and data compression is effective to reduce the indirect cost of the entire system on the premise that the potential values of the data are not affected.

G. Data Life Cycle Management

Generally speaking, values hidden in big data depend on data freshness. Therefore, a data importance principle related to the analytical value should be developed to decide which data shall be stored and which data shall be discarded.

H. Data in the Cloud

Database can be identified as a service as part of cloud computing. User access the cloud resources via network, in which users no more worry about the data storage and computing. Concerns have arosed afterwards about the data privacy, backaup and recovery since the isolation of users and data.

I. New Hardwares

Currently, most big data works on clusters of commodity machines. As the new technology in new hardware, like GPU, GPGPU, emerges, how to embrace these new hardware technology into big data is a new trend.

J. The Long Tails

As data becomes more and more important as computing. It has reached every corner of industry and all walks of life. Spatial and temporal databases are proposed in specific fields. The term "Small Data" is created to provide full and personal data management for individuals.

X. Conclusion

We have illustrated the BDMS from the perspective of a computer in five component.

We have entered an era of Big Data. Through better analysis of the large volumes of data that are becoming available, there is the potential for making faster advances in many scientific disciplines and improving the profitability and success of many enterprises. However, many technical challenges described in this paper must be addressed before this potential can be realized fully. The challenges include not just the obvious issues of scale, but also heterogeneity, lack of structure, error-handling, privacy, timeliness, provenance, and visualization, at all stages of the analysis pipeline from data acquisition to result interpretation. Furthermore, these challenges will require transformative solutions, and will not be addressed naturally by the next generation of industrial products. We must support and encourage fundamental research towards addressing these technical challenges if we are to achieve the promised benefits of Big Data.

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