Big Data Technologies and Cloud Computing

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2.1 The background and definition of big data

Nowadays, information technology opens the door through which humans step into a smart society and leads to the development of modern services such as: Internet e-commerce, modern logistics, and e-finance. It also promotes the development of emerging industries, such as Telematics, Smart Grid, New Energy, Intelligent Transportation, Smart City, and High-End Equipment Manufacturing. Modern information technology is becoming the engine of the operation and development of all walks of life. But this engine is facing the huge challenge of big data [1]. Various types of business data are growing by exponential orders of magnitude [2]. Problems such as data collection, storage, retrieval, analysis, and the application of data can no longer be solved by traditional information processing technologies. These issues have become great obstacles to the realization of a digital society, network society, and intelligent society. The New York Stock Exchange produces 1 terabyte (TB) of trading data every day; Twitter generates more than 7 TB of data every day; Facebook produces more than 10 TB of data every day; the Large Hadron Collider located at CERN produces about 15 PB of data every year. According to a study conducted by the well-known consulting firm International Data Corporation (IDC), the total global information volume of 2007 was about 165 exabytes (EB) of data. Even in 2009 when the global financial crisis happened, the global information volume reached 800 EB, which was an increase of 62% over the previous year. In the future, the data volume of the whole world will be doubled every 18 months. The number will reach 35 (zettabytes) ZB in 2020, about 230 times the number in 2007, yet the written record of 5000 years of human history amounts to only 5 EB data. These statistics indicate the eras of TB, PB, and EB are all in the past; global data storage is formally entering the “Zetta era.”

Beginning in 2009, “big data” has become a buzzword of the Internet information technology industry. Most applications of big data in the beginning were in the Internet industry: the data on the Internet is increasing by 50% per year, doubling
every 2 years. Most global Internet companies are aware of the advent of the “big data” era and the great significance of data. In May 2011, McKinsey Global Institute published a report titled “Big data: The next frontier for innovation, competition, and productivity” [3], and since the report was released, “big data” has become a hot topic within the computer industry. The Obama administration in the United States launched the “Big Data Research and Development Initiative” [4] and allocated $200 million specifically for big data in April 2012, which set off a wave of big data all over the world. According to the big data report released by Wikibon in 2011 [5], the big data market is on the eve of a growth spurt: the global market value of big data will reach $50 billion in the next five years. At the beginning of 2012, the total income of large data—related software, hardware, and services was around $5 billion. As companies gradually realize that big data and its related analysis will form a new differentiation and competitive advantage and will improve operational efficiency, big data—related technologies and services will see considerable development, and big data will gradually touch the ground and big data market will maintain a 58% compound annual growth rate over the next five years. Greg McDowell, an analyst with JMP Securities, said that the market of big data tools is expected to grow from $9 billion to $86 billion in 10 years. By 2020, investment in big data tools will account for 11% of overall corporate IT spending.

At present the industry does not have a unified definition of big data; big data has been defined in differing ways as follows by various parties:

*Big Data refers to datasets whose size is beyond the capability of typical database software tools to capture, store, manage, and analyze.*

—McKinsey.

*Big Data usually includes datasets with sizes beyond the capability of commonly used software tools to capture, curate, manage, and process the data within a tolerable elapsed time.*

—Wikipedia.

*Big Data is high volume, high velocity, and/or high variety information assets that require new forms of processing to enable enhanced decision making, insight discovery, and process optimization.*

—Gartner.

Big data has four main characteristics: Volume, Velocity, Variety, and Value [6] (referred to as “4V,” referencing the huge amount of data volume, fast processing speed, various data types, and low-value density). Following are brief descriptions for each of these characteristics.

Volume: refers to the large amount of data involved with big data. The scale of datasets keeps increasing from gigabytes (GB) to TB, then to the petabyte (PB) level; some even are measured with exabytes (EB) and zettabytes (ZB). For instance, the video surveillance cameras of a medium-sized city in China can produce tens of TB data every day.
Variety: indicates that the types of big data are complex. In the past, the data types that were generated or processed were simpler, and most of the data was structured. But now, with the emerging of new channels and technologies, such as social networking, the Internet of Things, mobile computing, and online advertising, much semi-structured or unstructured data is produced, in the form of text, XML, emails, blogs, and instant messages—as just a few examples—resulting in a surge of new data types. Companies now need to integrate and analyze data from complex traditional and nontraditional sources of information, including the companies’ internal and external data. With the explosive growth of sensors, smart devices, and social collaborative technologies, the types of data are uncountable, including text, microblogs, sensor data, audio, video, click streams, log files, and so on.

Velocity: The velocity of data generation, processing, and analysis continues to accelerate. There are three reasons: the real-time nature of data creation, the demands from combining streaming data with business processes, and decision-making processes. The velocity of data processing needs to be high, and processing capacity shifts from batch processing to stream processing. There is a “one-second rule” in the industry referring to a standard for the processing of big data, which shows the capability of big data processing and the essential difference between it and traditional data mining.

Value: Because of the enlarging scale, big data’s value density per unit of data is constantly reducing, however, the overall value of the data is increasing. Big data is even compared to gold and oil, indicating big data contains unlimited commercial value. According to a prediction from IDC research reports, the big data technology and services market will rise from $3.2 billion in 2010 to $16.9 billion in 2015, will achieve an annual growth rate of 40%, and will be seven times the growth rate of the entire IT and communication industry. By processing big data and discovering its potential commercial value, enormous commercial profits can be made. In specific applications, big data processing technologies can provide technical and platform support for pillar industries of the nation by analyzing, processing, and mining data for enterprises; extracting important information and knowledge; and then transforming it into useful models and applying them to the processes of research, production, operations, and sales. Meanwhile, many countries are strongly advocating the development of the “smart city” in the context of urbanization and information integration, focusing on improving people’s livelihoods, enhancing the competitiveness of enterprises, and promoting the sustainable development of cities. For developing into a “smart city,” a city would need to utilize the Internet of Things, Cloud computing, and other information technology tools comprehensively; integrate the city’s existing information bases; integrate advanced service concepts from urban operations; establish a widely deployed and deeply linked information network; comprehensively perceive many factors, such as resources, environment, infrastructures, and industries of the city; build a synergistic and shared urban information platform; process and utilize information intelligently, so as to provide intelligent response and control for city operation and resource allocation; provide the intelligent basis and methods for the decision making in social management and
public services; and offer intelligent information resources and open information platforms to enterprises and individuals.

Data is undoubtedly the cornerstone of the new IT services and scientific research, and big data processing technologies have undoubtedly become the hot spot of today’s information technology development. The flourishing of big data processing technologies also heralds the arrival of another round of the IT revolution. On the other hand—with the deepening of national economic restructuring and industrial upgrading—the role of information processing technologies will become increasingly prominent, and big data processing technologies will become the best breakthrough point for achieving advances in core technology, progress chasing, application innovation, and reducing lock-in in the informatization of the pillar industries of a nation’s economy [7].

2.2 Big data problems

Big data is becoming an invisible “gold mine” for the potential value it contains. With the accumulation and growth of production, operations, management, monitoring, sales, customer services, and other types of data, as well as the increase of user numbers, analyzing the correlation patterns and trends from the large amount of data makes it possible to achieve efficient management, precision marketing. This can be a key to opening this “gold mine.” However, traditional IT infrastructure and methods for data management and analysis cannot adapt to the rapid growth of big data. We summarize the problems of big data into seven categories in Table 2.1.

2.2.1 The problem of speed

Traditional relational database management systems (RDBMS) generally use centralized storage and processing methods instead of a distributed architecture. In many large enterprises, configurations are often based on IOE (IBM Server, Oracle Database, EMC storage). In the typical configuration, a single server’s configuration is usually very high, there can be dozens of CPU cores, and memory can reach the hundreds of GB. Databases are stored in high-speed and large-capacity disk arrays and storage space can be up to the TB level. The configuration can meet the demands of traditional Management Information Systems, but when facing ever-growing data volume and dynamic data usage scenarios, this centralized approach is becoming a bottleneck, especially for its limited speed of response. Because of its dependence on centralized data storage and indexing for tasks such as importing and exporting large amounts of data, statistical analysis, retrieval, and queries, its performance declines sharply as data volume grows, in addition to the statistics and query scenarios that require real-time responses. For instance, in the Internet of Things, the data from sensors can be up to billions of items; this data needs real-time storage, queries, and analysis; traditional RDBMS is no longer suitable for such application requirements.
2.2.2 The type and architecture problem

RDMBS has developed very mature models for the storage, queries, statistics, and processing of data that are structured and have fixed patterns. With the rapid development of the Internet of Things and Internet and mobile communication networks, the formats and types of data are constantly changing and developing. In the field of Intelligent Transportation, the data involved may contain text, logs, pictures, videos, vector maps, and various other kinds of data from different monitoring sources. The formats of this data are usually not fixed; it will be difficult to respond to changing needs if we adopt structured storage models. So we need to use various modes of data processing and storage and to integrate structured and unstructured data storage to process this data, whose types, sources, and structures are different. The overall data management model and architecture also require new types of distributed file systems and distributed NoSQL database architecture to adapt to large amounts of data and changing structures.

2.2.3 Volume and flexibility problems

As noted earlier—due to huge volume and centralized storage—there are problems with big data’s speed and response. When the amount of data increases and the
amount of concurrent read and write becomes larger and larger, a centralized file system or single database will become the deadly performance bottleneck. After all, a single machine can only withstand limited pressure. We can distribute the pressure to many machines up to a point at which they can withstand by adopting frameworks and methods with linear scalability, so the number of files or database servers can dynamically increase or decrease according to the amount of data and concurrence, to achieve linear scalability.

In terms of data storage, a distributed and scalable architecture needs to be adopted, such as the well-known Hadoop file system [8] and HBase database [9]. Meanwhile, in respect to data processing, a distributed architecture also needs to be adopted, assigning the data processing tasks to many computing nodes, in which we the correlation between the data storage nodes and the computing nodes needs to be considered. In the computing field, the allocation of resources and tasks is actually a task scheduling problem. Its main task is to make the best match between resources and tasks or among tasks, based on resource usage status (e.g., including the CPU, memory, storage, and network resources) of each individual node in the cluster and the Quality of Service (QoS) requirement of each user task. Due to the diversity of users’ QoS requirements and the changing status of resources, finding the appropriate resources for distributed data processing is a dynamic scheduling problem.

### 2.2.4 The cost problem

For centralized data storage and processing, when choosing hardware and software, a basic approach is to use very high-end mainframe or midrange servers and high-speed, high-reliability disk arrays to guarantee data processing performance. These hardware devices are very expensive and frequently cost up to several million dollars. For software, the products from large software vendors—such as Oracle, IBM, SAP, and Microsoft—are often chosen. The maintenance of servers and databases also requires professional technical personnel, and the investment and operation costs are high. In the face of the challenges of massive data processing, these companies have also introduced an “All-In-One” solution in the shape of a monster machine—such as Oracle’s Exadata or SAP’s Hana—by stacking multi-server, massive memory, flash memory, high-speed networks, and other hardware together to relieve the pressure of data. However, the hardware costs in such approaches are significantly higher than an ordinary-sized enterprise can afford.

The new distributed storage architecture and distributed databases—such as HDFS, HBase, Cassandra [10], MongoDB [11]—don’t have the bottleneck of centralized data processing and aggregation as they use a decentralized and massive parallel processing (MPP) architecture. Along with linear scalability, they can deal with the problems of storage and processing of big data effectively. For software architecture, they also have some automanagement and autohealing mechanisms to handle occasional failure in massive nodes and to guarantee the robustness of the overall system, so the hardware configuration of each node does not need to be high. An ordinary PC can even be used as a server, so the cost of servers can be
greatly reduced; in terms of software, open-source software also gives a very large price advantage.

Of course, we cannot make a simple comparison between the costs of hardware and software when we talk about cost problems. If we want to migrate systems and applications to the new distributed architecture, we must make many adjustments from the platforms in the bottom to the upper applications. Especially for database schema and application programming interfaces, there is a big difference between NoSQL databases and the original RDBMS; enterprises need to assess the cost, cycle, and risk of migration and development. Additionally, they also need to consider the cost from service, training, operation, and maintenance aspects. But in general the trend is for these new data architectures and products to become better developed and more sophisticated, as well as for some commercial operating companies to provide professional database development and consulting services based on open source. The new distributed, scalable database schema is, therefore, bound to win in the big data wave, defeating the traditional centralized mainframe model in every respect: from cost to performance.

2.2.5 The value mining problem

Due to huge and growing volumes, the value density per data unit is constantly shrinking, while the overall value of big data is steadily increasing. Big data is analogous to oil and gold, so we can mine its huge business value [12]. If we want to extract the hidden patterns from large amount of data, we need deep data mining and analysis. Big data mining is also quite different from traditional data mining models. Traditional data mining generally focuses on moderate data size and its algorithm is relatively complex and convergence is slow, while in big data the quantity of data is massive and the processes of data storage, data cleaning, and ETL (extraction, transformation, loading) deal with the requirements and challenges of massive volume, which generally suggests the use of distributed and parallel processing models. For example, in the case of Google and Microsoft’s search engines, hundreds or even thousands of servers working synchronously are needed to perform the archive storage of users’ search logs generated from search behaviors of billions of worldwide users. Similarly, when mining the data, we also need to restructure traditional data mining algorithms and their underlying processing architectures, adopting the distributed and parallel processing mechanism to achieve fast computing and analysis over massive amounts of data. For instance, Apache’s Mahout [13] project provides a series of parallel implementations of data mining algorithms. In many application scenarios, the mining results even need to be returned in real time, which poses significant challenges to the system: data mining algorithms usually take a long time, especially when the amount of data is huge. In this case, maybe only a combination of real-time computation and large quantities of offline processing can meet the demand.

The actual gain from data mining is an issue to be carefully assessed before mining big data’s value, as well as the awareness that not all of the data mining programs will lead to the desired results. Firstly, we need to guarantee the authenticity
and completeness of the data. For example, if the collection of information introduces big noise itself, or some key data is not included, the value that is dug out will be undermined. Second, we also need to consider the cost and benefit of the mining. If the investments of manpower and hardware and software platforms are costly and the project cycle is long, but the information extracted is not very valuable for an enterprise’s production decisions or cost-effectiveness, then the data mining is impractical and not worth the effort.

2.2.6 The security and privacy problem

From the perspective of storage and safety reliability, big data’s diverse formats and huge volume have also brought a lot of challenges. For structured data, RDBMSs have already formed a set of comprehensive mechanisms for storage, access, security, and backup control after decades of development. The huge volume of big data has impacted traditional RDBMS: centralized data storage and processing are shifting to distributed parallel processing, as already mentioned. In most cases, big data is unstructured data, thus a lot of distributed file storage systems and distributed NoSQL databases are derived to deal with this kind of data. But such emerging systems need to be further developed, especially in areas such as user management, data access privileges, backup mechanisms, and security controls. Security, in short, first is the prevention of data loss, which requires reasonable backup and redundancy mechanisms for the massive volume of structured and unstructured data, so data will never be lost under any circumstances. Second, security refers to protecting the data from unauthorized access. Only the users with the right privileges and permissions can see and access the data. Since large amounts of unstructured data may require different storage and access mechanisms, a unified security access control mechanism for multisource and multitype data has yet to be constructed and become available. Because big data means more sensitive data is put together, it’s more attractive to potential hackers: a hacker will be able to get more information if he manages a successful attack—the “cost performance ratio” is higher. All of these issues make it easier for big data to become the target of attack. In 2012, LinkedIn was accused of leaking 6.5 million user account passwords; Yahoo! faced network attacks, resulting in 450,000 user ID leaks. In December 2011, Chinese Software Developer Network’s security system was hacked, and 6,000,000 user login names, passwords, and email addresses were leaked.

Privacy problems are also closely associated with big data. Due to the rapid development of Internet technology and the Internet of Things, all kinds of information related to our lives and jobs have been collected and stored. We are always exposed to the “third eye.” No matter when we are surfing the Internet, making a phone call, writing microblogs, using Wechat, shopping, or traveling, our actions are always being monitored and analyzed. The in-depth analysis and modeling of user behaviors can serve customers better and make precision marketing possible. However, if the information is leaked or abused, it is a direct violation to the user’s privacy, bringing adverse effects to users, and even causing life and property loss.
In 2006, the US DVD rental company Netflix organized an algorithm contest. The company released a million renting records from about 500,000 users, and publicly offered a reward of one million dollars, organizing a software design contest to improve the accuracy of their movie recommendation system; with the condition of victory was an improvement in their recommendation engine’s accuracy by 10%. Although the data was carefully anonymized by the company, a user was still identified and disclosed by the data; a closeted lesbian mother, going by the name “Anonymous” sued Netflix. She came from the conservative Midwest. On Twitter, com, a popular site in the United States, many users are accustomed to publishing their locations and activities at any time. There are a few sites, such as “PleaseRobMe.com” and “WeKnowYourHouse.com,” that can speculate the times that the users are not at home, get the user’s exact home address, and even find photos of the house, just based on the information the users published. Such Web sites are designed to warn us that we are always exposed to the public eye; if we don’t develop an awareness of safety and privacy, we will bring disaster upon ourselves. Nowadays, many countries around the world—including China—are improving laws related to data use and privacy to protect privacy information from being abused.

2.2.7 Interoperability and data sharing issues

In the process of enterprise information development in China, fragmentation and information-silos are common phenomena. Systems and data between different industries have almost no overlap, while within an industry—such as within the transportation and social security systems—they are divided and constructed by administrative regions such that information exchange and collaboration across regions are very difficult. More seriously, even within the same unit—such as in the development of information systems within a district hospital—subsystems for data such as medical record management, bed information, and drug management are developed discretely, and there is no information sharing and no interoperability. “Smart City” is one of the key components in China’s Twelfth Five-Year Plan for information development. The fundamental goals of “Smart City” are: to achieve interoperability and the sharing of information, so as to realize intelligent e-government, social management, and improvement in people’s lives. Thus, in addition to creating a Digital City where information and data are digitized, we also need to establish interconnection—to open access to the data interfaces of all disciplines, so as to achieve interoperability—and then to develop intelligence. For example, in the emergency management of urban areas, we need data and assistance from many departments and industries, such as: transportation, census, public security, fire, and health care. At present the data sharing platform developed by the US federal government, www.data.gov, and the data resource Network of Beijing Municipal Government, www.bjdata.gov.cn, are great moves toward open access to data and data sharing.

To achieve cross-industry data integration, we need to make uniform data standards and exchange interfaces as well as sharing protocols, so we can access, exchange, and share data from different industries, different departments, and
different formats on a uniform basis. For data access, we also need to have detailed access control to regulate which users can access which type of data under what circumstances. In the big data and Cloud computing era, data from different industries and enterprises may be stored on a single platform and data center, and we need to protect sensitive information—such as data related to corporate trade secrets and transaction information. Although their processing relies on the platform, we should require that—other than authorized personnel from the enterprises—platform administrators and other companies cannot gain access to such data.

2.3 The dialectical relationship between Cloud computing and big data

Cloud computing has development greatly since 2007. Cloud computing’s core model is large-scale distributed computing, providing computing, storage, networking, and other resources to many users in service mode, and users can use them whenever they need them [14]. Cloud computing offers enterprises and users high scalability, high availability, and high reliability. It can improve resource utilization efficiency and can reduce the cost of business information construction, investment, and maintenance. As the public Cloud services from Amazon, Google, and Microsoft become more sophisticated and better developed, more and more companies are migrating toward the Cloud computing platform.

Because of the strategic planning needs of the country as well as positive guidance from the government, Cloud computing and its technologies have made great progress in recent years in China. China has set up models in several cities, including Beijing, Shanghai, Shenzhen, Hangzhou, and Wuxi. Beijing’s “Lucky Cloud” plan, Shanghai’s “CloudSea” plan, Shenzhen’s “International Joint Laboratory of Cloud Computing,” Wuxi’s “Cloud Computing Project,” and Hangzhou’s “West Lake Cloud Computing Platform for Public Service” have been launched. Other cities, such as Tianjin, Guangzhou, Wuhan, Xi’an, Chongqing, and Chengdu, have also introduced corresponding Cloud computing development plans or have set up Cloud computing alliances to carry out research, development, and trials of Cloud computing. But the popularity of Cloud computing in China is still largely limited by infrastructure and a lack of large-scale industrial applications, so Cloud computing has not yet gained its footing. The popularity of the Internet of Things and Cloud computing technology relate to the idea that they are humanity’s great vision, so that it can achieve large-scale, ubiquitous, and collaborative information collection, processing, and application. However, it is based on the premise that most industries and enterprises have good foundations and experience in informatization and have the urgent need to transform the existing system architecture and to improve the efficiency of the system. The reality is that most of China’s Small and Medium Enterprises have only just begun in the area of informatization, and only a few large companies and national ministries have the necessary foundation in information development.
The outbreak of big data is a thorny problem encountered in social and informatization development. Because of the growth of data traffic and data volume, data formats are now multisource and heterogeneous, and they require real-time and accurate data processing. Big data can help us discover the potential value of large amounts of data. Traditional IT architecture is incapable of handling the big data problem, as there are many bottlenecks, such as: poor scalability; poor fault tolerance; low performance; difficulty in installation, deployment, and maintenance; and so on. Because of the rapid development of the Internet of Things, the Internet, and mobile communication network technology in recent years, the frequency and speed of data transmission has greatly accelerated. This gives rise to the big data problem, and the derivative development and deep recycling use of data make the big data problem even more prominent.

Cloud computing and big data are complementary, forming a dialectical relationship. Cloud computing and the Internet of Things’ widespread application is people’s ultimate vision, and the rapid increase in big data is a thorny problem that is encountered during development. The former is a dream of humanity’s pursuit of civilization, the latter is the bottleneck to be solved in social development. Cloud computing is a trend in technology development, while big data is an inevitable phenomenon of the rapid development of a modern information society. To solve big data problems, we need modern means and Cloud computing technologies. The breakthrough of big data technologies can not only solve the practical problems, but can also make Cloud computing and the Internet of Things’ technologies land on the ground and be promoted and applied in in-depth ways.

From the development of IT technologies, we can summarize a few patterns:

1. The competition between Mainframe and personal PCs ended in the PC’s triumph. The battle between Apple’s iOS and the Android, and the open Android platform has taken over more than 2/3 of market share in only a couple of years. Nokia’s Symbian operating system is on the brink of oblivion because it is not open. All of these situations indicate that modern IT technologies need to adopt the concept of openness and crowdsourcing to achieve rapid development.

2. The collision of existing conventional technologies with Cloud computing technology is similar to the aforementioned situations; the advantage of Cloud computing technology is its utilization of the crowdsourcing theory and open-source architecture. Its construction is based on a distributed architecture of open platform and novel open-source technologies, which allow it to solve problems that the existing centralized approach is difficult to solve or cannot solve. TaoBao, Tencent, and other large Internet companies once also relied on proprietary solutions provided by big companies such as Sun, Oracle, and EMC. Then they abandoned those platforms because of the cost and adopted open-source technologies. Their products have also, in turn, ultimately contributed to the open-source community, reflecting the trend in information technology development.

3. The traditional industry giants are shifting toward open-source architecture; this is a historic opportunity for others to compete. Traditional industry giants and large state enterprises—such as the National Grid, telecommunications, banking, and civil aviation—rely too heavily on sophisticated proprietary solutions provided by foreign companies for historical reasons, resulting in a pattern that lacks innovation and has been hijacked by foreign products. Analyzing from the perspective of the path and the plan to solve the big
data problem, we must abandon the traditional IT architecture gradually, and must begin to utilize the new generation of information technology represented by Cloud technology. Despite the fact that advanced Cloud computing technology originated mainly in the United States, because of open-source technology, the gap between Chinese technology and the advanced technology is not large. The urgent big data problem of applying Cloud computing technologies to large-scale industry is also China’s historic opportunity to achieve breakthrough innovations, defeat monopolies, and catch up with international advanced technologies.

2.4 Big data technologies

Big data brings not only opportunities but also challenges. Traditional data processing has been unable to meet the massive real-time demand of big data; we need the new generation of information technology to deal with the outbreak of big data. Table 2.2 classifies big data technologies into five categories.

*Infrastructure support*: mainly includes infrastructure-level data center management, Cloud computing platforms, Cloud storage equipment and technology, network technology, and resource monitoring technology. Big data processing needs the support from Cloud data centers that have large-scale physical resources and

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Cloud computing platforms that have efficient scheduling and management functionalities.

*Data acquisition*: data acquisition technology is a prerequisite for data processing; first we need the means of data acquisition for collecting the information and then we can apply top-layer data processing technologies to them. Besides the various types of sensors and other hardware and software equipment, data acquisition involves the ETL (extraction, transformation, loading) processing of data, which is actually preprocessing, which includes cleaning, filtering, checking and conversion, and converting the valid data into suitable formats and types. Meanwhile, to support multisource and heterogeneous data acquisition and storage access, a enterprise data bus is needed to facilitate the data exchange and sharing between the various enterprise applications and services.

*Data storage*: after collection and conversion, data needs to be stored and archived. Facing the large amounts of data, distributed file storage systems and distributed databases are generally used to distribute the data to multiple storage nodes, and are also needed to provide mechanisms such as backup, security, access interfaces, and protocols.

*Data computing*: data queries, statistics, analysis, forecasting, mining, graph analysis, business intelligence (BI), and other relevant technologies are collectively referred to as data computing technologies. Data computing technologies cover all aspects of data processing and utilize the core techniques of big data technology.

*Display and interaction*: display of data and interaction with data are also essential in big data technologies, since data will eventually be utilized by people to provide decision making support for production, operation, and planning. Choosing an appropriate, vivid, and visual display can give a better understanding of the data, as well as its connotations and associated relationships, and can also help with the interpretation and effective use of the data, to fully exploit its value. For the means of display, in addition to traditional reporting forms and graphics, modern visualization tools and human—computer interaction mechanisms—or even Augmented Reality (AR) technology, such as Google Glasses—can be used to create a seamless interface between data and reality.

2.4.1 **Infrastructure support**

Big data processing needs the support of cloud data centers that have large-scale physical resources and Cloud computing platforms that have efficient resource scheduling and management. Cloud computing management platforms can: provide flexible and efficient deployment, operation, and management environments for large data centers and enterprises; support heterogeneous underlying hardware and operating systems with virtualization technology; provide applications with cloud resource management solutions that are secure, high performance, highly extensible, highly reliable, and highly scalable; reduce the costs of application development, deployment, operation, and maintenance; and improve the efficiency of resource utilization.
As a new computing model, Cloud computing has gained great momentum in both academia and industry. Governments, research institutions, and industry leaders are actively trying to solve the growing computing and storage problems in the Internet age using Cloud computing. In addition to Amazon Web Services (AWS), Google’s App Engine, and Microsoft’s Windows Azure Services—along with other commercial cloud platforms—there are also many open-source Cloud computing platforms, such as: OpenNebula [15,16], Eucalyptus [17], Nimbus [18], and OpenStack [19]. Each platform has its own significant features and constantly evolving community.

AWS is the most popular Cloud computing platform; in the first half of 2013, its platform and Cloud computing services have earned $1.7 billion, with year-on-year growth of 60%. The most distinct features of its system architecture are open data, functioning via Web Service interfaces, and the achievement of loose-coupling via Service Oriented Architecture (SOA). The web service stack AWS provides can be divided into four layers:

1. The Access Layer: provides management console, API, and various command-line tools.
2. The Common Service Layer: includes authentication, monitoring, deployment, and automation.
3. The PaaS Layer: includes parallel processing, content delivery, and messaging services.
4. The IaaS Layer: includes Cloud computing platform EC2, Cloud storage services S3/EBS, network services VPC/ELB, and database services.

Eucalyptus is an open-source Cloud computing platform that attempts to clone AWS. It has realized functionalities similar to Amazon EC2, achieving flexible and practical Cloud computing with computing clusters and workstation clusters; it provides compatibility interfaces for EC2 and S3 systems. The applications that use these interfaces can interact directly with Eucalyptus, and it supports Xen [20] and KVM [21] virtualization technology, as well as Cloud management tools for system management and user account settlements. Eucalyptus consists of five major components, namely, cloud controller CLC, cloud storage service Walrus, cluster controller CC, storage controller SC, and node controller NC. Eucalyptus manages computing resources by way of “Agents”: components that can collaborate together to provide the required Cloud services.

OpenNebula is an open-source implementation of the virtualization management of virtual infrastructure and Cloud computing initiative by the European Research Institute in 2005. It’s an open-source tool used to create IaaS private Clouds, public Clouds, and hybrid Clouds, and is also a modular system that can create different Cloud architectures and interact with a variety of data center services. OpenNebula has integrated storage, network, virtualization, monitoring, and security technologies. It can deploy multilayered services in a distributed infrastructure in the form of virtual machines according to allocation policies. OpenNebula can be divided into three layers: the interface layer, the core layer, and the driver layer.

1. The interface layer provides native XML-RPC interfaces and implements various APIs, such as: EC2, Open Cloud Computing Interface, and OpenNebula Cloud API, giving users a variety of access options.
2. The core layer provides core functionalities such as unified plug-in management, request management, VM lifecycle management, hypervisor management, network resources management, and storage resource management in addition to others.

3. The final layer is the driver layer. OpenNebula has a set of pluggable modules to interact with specific middleware (e.g. virtualization hypervisor, cloud services, file transfer mechanisms or information services), these adaptors are called Drivers.

OpenStack is an open-source Cloud computing virtualization infrastructure with which users can build and run their Cloud computing and storage infrastructure. APIs compatible with Amazon EC2/S3 allows users to interact with Cloud services provided by OpenStack, and it also allows client tools written for AWS to work with OpenStack. OpenStack is among the best as far as the implementation of SOA and the decoupling of service-oriented components. The overall architecture of OpenStack is also divided into three layers. The first layer is the access layer for applications, management portals (Horizon), and APIs; the core layer comprises computing services (Nova), storage services (including the object storage service Swift and block storage service Cinder), and network services (Quantum); layer 3 is for shared services, which now includes identity management service (keystone) and image service (Glance).

Nimbus System is an open-source system, providing interfaces that are compatible with Amazon EC2. It can create a virtual machine cluster promptly and easily so that a cluster scheduling system can be used to schedule tasks, just like in an ordinary cluster. Nimbus also supports different virtualization technologies (XEN and KVM). It is mainly used in scientific computing.

### 2.4.2 Data acquisition

Sufficient scale of data is the basis of big data strategic development for enterprises, so data acquisition has become the first step of big data analysis. Data acquisition is an important part of the value mining of big data, and the subsequent analysis and data mining rely on it. The significance of big data is not in grasping the sheer scale of the data, but rather in the intelligent processing of the data—the analysis and mining of valuable information from it—but the premise is to have a large amount of data. Most enterprises have difficulty judging which data will become data assets in the future and the method for refining the data into real revenue. For this, even big data service vendors cannot give a definitive answer. But one thing is for sure: in the era of big data, one who has enough data is likely to rule the future: the acquisition of big data now is the accumulation of assets for the future.

Data acquisition can be accomplished via sensors in the Internet of Things and also can be derived from network information. For example, in Intelligent Transportation, data acquisition may include information collection based on GPS positioning, image collection based on traffic crossroads, and coil signal collection based on intersections. Data acquisition on the Internet, in contrast, collects a variety of page and user visit information from various network media, such as: search engines, news sites, forums, microblogs, blogs, and e-commerce sites, and the contents are mainly text, URL, access logs, dates, and pictures. Preprocessing,
such as: cleaning, filtering, and duplicate removal, is then needed, followed by categorization, summarization, and archiving.

ETL tools are responsible for extracting the different types and structures of data from distributed, heterogeneous data sources, such as: text data, relational data, pictures, video, and other unstructured data, to a temporary middle layer to clean, convert, classify, integrate, and finally load them into the corresponding data storage systems. These systems include data warehouses and data marts, which serve as the basis for online analytical processing and data mining. ETL tools for big data are different from the traditional ETL process: on the one hand, the volume of big data is huge, on the other hand, the data’s production speed is very fast. For example, video cameras and smart meters in a city generate large amounts of data every second, thus preprocessing of data has to be real-time and fast. When choosing ETL architecture and tools, a company also adopts modern information technology, such as: distributed memory databases, real-time stream processing systems.

There are various applications and various data formats and storage requirements for modern enterprises, but between enterprises and within enterprises, there exists the problems of fragmentation and information islands. Enterprises cannot always easily achieve controlled data exchange and sharing, and the limitations of development technologies and environments also set up barriers to enterprise data sharing. This can hinder data exchange and sharing between applications and the enterprise’s ability to control, manage, and secure data. To achieve cross-industry and cross-departmental data integration—especially in the development of a Smart City—we need to develop unified data standards as well as exchange interfaces and sharing protocols, so data from different industries and different departments with different formats can be accessed, exchanged, and shared based in a unified way. With enterprise data bus (EDS), we can provide data access functions to all kinds of data and can separate the enterprise’s data access integration from the enterprise’s functional integration.

EDS creates an abstraction layer for data access, so corporate business functions can avoid the details of data access. Business components only need to contain service function components (used to implement services) and data access components (by the use of EDS). By means of EDS, we can provide a unified data conversion interface between the data models for enterprise management and application systems, and can effectively reduce coupling between the various application services. In big data scenarios, there are a large number of synchronized data access requests in EDS. The performance degradation of any module in the bus will greatly affect the functionality of the bus, so EDS needs to be implemented in a large-scale, concurrent, and highly scalable way as well.

2.4.3 Data storage

Big data is accumulating large amounts of information each year. Combined with existing historical data information, it has brought great opportunities and challenges to the data storage and data processing industry. In order to meet the fast-growing storage demand, Cloud storage requires high scalability, high reliability,
high availability, low cost, automatic fault tolerance, and decentralization. Common forms of Cloud storage can be divided into distributed file systems and distributed databases. Distributed file systems use large-scale distributed storage nodes to meet the needs of storing large amounts of files, and distributed NoSQL databases support the processing and analysis of massive amounts of unstructured data.

Early on when Google was facing the problems of storage and analysis of large numbers of Web pages, it developed Google File System (GFS) [22] and the MapReduce distributed computing and analysis model [23–25] based on GFS. Since some applications need to deal with a large amount of formatted and semi-formatted data, Google also built a large-scale database system called BigTable [26], which supports weak consistency and is capable of indexing, querying, and analyzing massive amounts of data. This series of Google products has opened the door to massive data storage, querying, and processing in the Cloud computing era, and has become the de facto standard in this field, with Google remaining a technology leader.

Google’s technology was not open source, so Yahoo and open-source communities developed Hadoop system collaboratively, which is an open-source implementation of MapReduce and GFS. The design principles of its underlying file system HDFS is completely consistent with GFS, and an open-source implementation of BigTable is also provided, which is a distributed database system named HBase. Since their launch, Hadoop and HBase have been widely applied all over the world. They are now managed by the Apache Foundation. Yahoo’s own search system runs on Hadoop clusters of hundreds of thousands of servers.

GFS has fully considered the harsh environment it faces in running a distributed file system in a large-scale data cluster:

1. A large number of nodes may encounter failure so fault tolerance and automatic recovery functions may need to be integrated into the system.
2. Construct special file system parameters: files are usually measured in GB, and there may be a large number of small files.
3. Consider the characteristics of applications, support file append operations, optimize sequential read and write speeds.
4. Some specific operations of the file system are no longer transparent and need the assistance of application programs.

Figure 2.1 depicts the architecture of the GFS: a GFS cluster contains a primary server (GFS Master) and several chunk servers, which are accessed by multiple clients (GFS Client). Large files are split into chunks with fixed sizes; a chunk server stores the blocks on local hard drives as Linux files and reads and writes chunk data according to specified chunk handles and byte ranges. In order to guarantee reliability, each chunk has three replicas by default. The Master server manages all of the metadata of the file system, including namespaces, access control, mapping of files to chunks, physical locations of chunks, and other relevant information. By joint design of the server side and client side, GFS provides applications with optimal performance and availability support. GFS was designed for Google applications themselves; there are many deployments of GFS clusters in Google. Some clusters have
more than a thousand storage nodes, storage space over PB, and are visited by thousands of clients continuously and frequently from different machines.

In order to deal with massive data challenges, some commercial database systems attempt to combine traditional RDBMS technologies with distributed, parallel computing technologies to meet the requirements of big data. Many systems also try to accelerate data processing on the hardware level. Typical systems include IBM’s Netezza, Oracle’s Exadata, EMC’s Greenplum, HP’s Vertica, and Teradata. From a functionality perspective, these systems can continue supporting the operational semantics and analysis patterns of traditional databases and data warehouses. In terms of scalability, they can also use massive cluster resources to process data concurrently, dramatically reducing the time for loading, indexing, and query processing of data.

Exadata and Netezza have both adopted data warehouse AIO solutions. By combining software and hardware together, they have a seamlessly integrated database management system (DBMS), servers, storage, and networks. For users, an AIO machine can be installed quickly and easily, and can satisfy users’ needs via standard interfaces and simple operations. These AIO solutions have many shortcomings, too, though, including expensive hardware, large energy consumption, expensive system service fees, and the required purchase of a whole system when upgrade is needed. The biggest problem of Oracle’s Exadata is the Shared-Everything architecture, resulting in limited IO processing capacity and scalability. The storage layers in Exadata cannot communicate with each other, so any results of intermediate computing have to be delivered from the storage layer to the RAC node, then delivered to the corresponding storage layer node by the RAC node, and

Figure 2.1 Architecture of the GFS.
before it can be computed. The large number of data movements results in unnecessary IO and network resource consumption. Exadata’s query performance is not stable; its performance tuning also requires experience and in-depth knowledge.

NoSQL databases by definition break the paradigm constraints of traditional relational databases. From a data storage perspective, many NoSQL databases are not relational databases, but are hash databases that have key-value data format. Because of the abandonment of the powerful SQL query language, transactional consistency, and normal form constraints of relational databases, NoSQL databases can solve challenges faced by traditional relational databases to a great extent. In terms of design, they are concerned with high concurrent reading and writing of data and massive amounts of data storage. Compared with relational databases, they have a great advantage in scalability, concurrency, and fault tolerance. Mainstream NoSQL databases include Google’s BigTable, an open-source implementation similar to BigTable named HBase, and Facebook’s Cassandra.

As some Google applications need to process a large number of formatted and semi-formatted data, Google built a large-scale database system with weak consistency named BigTable. BigTable applications include search logs, maps, an Orkut online community, an RSS reader, and so on.

Figure 2.2 describes the data model of BigTable. The data model includes rows, columns, and corresponding timestamps, with all of the data stored in the cells. BigTable contents are divided by rows, and many rows form a tablet, which is saved to a server node.

Similar to the aforementioned systems, BigTable is also a joint design of client and server, making performance meet the needs of applications. The BigTable system relies on the underlying structure of a cluster system, a distributed cluster task scheduler, and the GFS, as well as a distributed lock service Chubby. Chubby is a very robust coarse-grained lock, which BigTable uses to store the bootstrap location of BigTable data, thus users can obtain the location from Chubby first, and then access the data. BigTable uses one server as the primary server to store and manipulate metadata. Besides metadata management, the primary server

![Figure 2.2 Data model in BigTable.](image-url)
is also responsible for remote management and load deployment of the tablet server (the general sense of the data server). Client uses the programming interfaces for metadata communication with the main server and data communication with tablet servers.

As for large-scale distributed databases, mainstream NoSQL databases—such as HBase and Cassandra—mainly provide high scalability support and make some sacrifices in consistency and availability, as well as lacking traditional RDBMS ACID semantics and transaction support. Google Megastore [27], however, strives to integrate NoSQL with a traditional relational database and to provide a strong guarantee for consistency and high availability. Megastore uses synchronous replication to achieve high availability and consistent view of the data. In short, Megastore provides complete serialized ACID semantics for “low-latency data replicas in different regions” to support interactive online services. Megastore combines the advantages of NoSQL and RDBMS, and can support high scalability, high fault tolerance, and low latency while maintaining consistency, providing services for hundreds of production applications in Google.

### 2.4.4 Data computing

Data queries, statistics, analysis, mining, and other requirements for big data processing have motivated different computing models of big data, and we divide big data computing into three categories: offline batch computing, real-time interactive computing, and stream computing.

#### 2.4.4.1 Offline batch computing

With the widespread application and development of Cloud computing technologies, analysis systems based on open-source Hadoop distributed storage system and MapReduce data processing mode have also been widely used. Hadoop can support PB levels of distributed data storage through data partitioning and an auto-recovery mechanism, and can analyze and process this data based on MapReduce’s distributed processing model. The MapReduce programming model can easily make many general data batch processing tasks and operations parallel on a large-scale cluster and can have automated failover capability. Led by open-source software such as Hadoop, the MapReduce programming model has been widely adopted and is applied to Web search, fraud detection, and a variety of other practical applications.

Hadoop is a software framework that can achieve distributed processing of large amounts of data in a way that is reliable, efficient, and scalable, relying on horizontal scaling to improve computing and storage capacity by adding low-cost commodity servers. Users can easily develop and run applications for massive data. We summarize Hadoop’s advantages as follows:

1. High reliability: data storage and processing is worthy of trust.
2. High scalability: data allocation and computing task completion occurs in available computer clusters, and these clusters can be expanded to the scale of thousands of nodes easily.
3. High efficiency: data can be dynamically moved between nodes and the dynamic balance of each node is ensured, thus the processing speed is very fast.

4. High fault-tolerance: multiple copies of data can be saved automatically and failed tasks are reassigned automatically.

Big data processing platform technologies [28] utilizing the Hadoop platform include MapReduce, HDFS, HBase, Hive, Zookeeper, Avro [29], and Pig, which has formed a Hadoop ecosystem, as shown in Figure 2.3.

1. The MapReduce programming model is the heart of Hadoop and is used for the parallel computation of massive datasets. It is this programming model that has achieved massive scalability across hundreds or thousands of servers within a Hadoop cluster.

2. Distributed File System HDFS provides mass data storage based on the Hadoop processing platform. NameNode provides metadata services, and DataNode is used to store the file blocks of the file system.

3. HBase is built on HDFS and is used to provide a database system that has high reliability, high performance, column storage, scalability, and real-time read and write. It can store unstructured and semi-structured sparse data.

4. Hive [30] is a large data warehouse based on Hadoop that can be used for data extraction, transformation, and loading (ETL); storage; querying; and analysis of large-scale data stored in Hadoop.

5. Pig [31] is a large-scale data analysis platform based on Hadoop that can transform SQL-like data analysis requests into a series of optimized MapReduce operations and can provide a simple operation and programming interface for complex massive data parallel computing.

6. Zookeeper [32] is an efficient and reliable collaborative system; it is used to coordinate a variety of services on distributed applications. Zookeeper can be used to build a coordination service that can prevent single-point failures and can deal with load balancing effectively.

7. As high performance, binary communication middleware, Avro provides data serialization capabilities and RPC services between Hadoop platforms.

The Hadoop platform is mainly for offline batch applications and is typically used to schedule batch tasks on static data. The computing process is relatively [Figure 2.3 The Hadoop ecosystem.]
slow. To get results, some queries may take hours or even longer, so it is impotent when faced with applications and services with real-time requirements. MapReduce is a good cluster parallel programming model and can meet the needs of a majority of applications. Although MapReduce is a good abstract of distributed/parallel computing, it is not necessarily suitable for solving any computing problem. For example, for those applications that require results in real time, such as advertisement placement based on the pay-per-click traffic model, social recommendations based on real-time data analysis of users’ behavior, or anti-fraud statistics based on Web search and clickstream, MapReduce cannot provide efficient processing for these real-time applications because the processing of the application logic requires multiple rounds of tasks—or the splitting of the input data into a fine grain. The MapReduce model has the following limitations:

1. The intermediate data transfer is difficult to be fully optimized.
2. The restart of individual tasks is costly.
3. The storage cost for intermediate data is high.
4. The master node can easily become a bottleneck.
5. Support is limited to a unified file chunk size, which makes it difficult to deal with a complex collection of documents that have a variety of sizes.
6. Structured data is difficult to store and access directly.

In addition to the MapReduce computing model, workflow computing models represented by Swift [33,34] and graph computing models represented by Pregel [35] can handle application processes and graph algorithms that contain large-scale computing tasks. As a bridge between scientific workflow and parallel computing, the Swift system is a parallel programming tool for fast and reliable specification, execution, and management of large-scale science and engineering workflows. Swift uses a structured approach to manage workflow definition, scheduling, and execution. It uses the simple scripting language SwiftScript. SwiftScript can concisely describe complex parallel computing [36] based on dataset types and iterations. Meanwhile, it can dynamically map datasets for large-scale data with different data formats. When it is running, the system provides an efficient workflow engine for scheduling and load balancing, and it can interact with resource management systems, such as PBS and Condor, to execute the tasks. Pregel is a distributed programming framework for graph algorithms that can be used in graph traversal, shortest path, and PageRank computing. It adopts the iterative computing model: In each round, every vertex processes the messages that are received in the last round, sends messages to other vertices, and updates status and topology (outgoing edges, incoming edges).

2.4.4.2 Real-time interactive computing

Nowadays, real-time computing generally needs to process large amounts of data, in addition to meeting some of the requirements of non-real-time computing (e.g., accurate results). The most important requirement of real-time computing is the response to computing results in real time—generally at the millisecond level.
Real-time computing can generally be categorized into the following two application scenarios:

1. The amount of data is huge and the results cannot be computed in advance, while user response has to be in real time.
   It is mainly used for specific data analysis and processing. When the amount of data is large and it is impossible to list all query combinations for possible conditions or the exhaustive condition combinations do not help, then real-time computing can play a role in postponing the computing process until the query phase, though it needs to provide users with real-time responses. In this case, it can process part of the data in advance and combine it with the real-time computing results to improve processing efficiency.

2. The data source is real-time and continuous and requires user response to be real time.
   When the data source is real time and continuous, it is called streaming data. So-called streaming data means the data is viewed as a data stream. A data stream is a collection of a series of data records that are unbounded in time distribution and number. A data record is the smallest unit of data streams. For example, the data generated by sensors of the Internet of Things may be continuous. We will introduce stream processing systems in the next section separately. Real-time data computing and analysis can analyze and count data dynamically and in real time, this has important practical significance on system monitoring, scheduling, and management.

The real-time computing process of massive data can be divided into the following three phases: real-time data collection, real-time data analysis and processing, and real-time query services, as shown in Figure 2.4.

**Real-time data collection**: It must ensure collection of all of the data and must provide real-time data for real-time applications. Response time must be real time and low latency. Configuration should be simple and deployment should be easy. The system needs to be stable and reliable. Currently, big data acquisition tools from Internet companies include Facebook’s open-source Scribe [37], LinkedIn’s open-source Kafka [38], Cloudera’s open-source Flume [39], Taobao’s open-source TimeTunnel [40], and Hadoop’s Chukwa [41], which can all meet the acquisition and transmission requirements for log data, which is hundreds of megabytes (MB) per second.

**Real-time data computing**: Traditional data operations usually include collecting data and storing it in a DBMS first, then interacting with DBMS via queries to get the answers users want. Throughout the entire process the users are active, while the DBMS system is passive. However, for real-time big data, which requires real-timeliness, huge data volume, and diverse data formats, traditional relational database architecture is not suitable. The new real-time computing architectures generally adopt the distributed architecture of MPP, and data storage and processing are then assigned to large-scale nodes to meet the real-time requirements. For data
storage they use large-scale distributed file systems, such as Hadoop’s HDFS file system or the new NoSQL distributed databases.

**Real-time query service:** Its implementation can be categorized in three ways: (1) Full Memory, which provides data read services directly, and dumps to disks or databases for backup regularly. (2) Semi-Memory, which uses Redis, Memcache, MongoDB, BerkeleyDB, and other databases to provide real-time querying services and leaves backup operations to these systems. (3) Full Disk, which uses NoSQL databases such as HBase that are based on distributed file system (HDFS). As for key-value engines, it is vital to design the distribution of the key.

Among real-time and interactive computing technologies, Google’s Dremel [36] system is the most prominent. Dremel is Google’s “interactive” data analysis system. It can build clusters of scale of thousands and can process PB-level data. As the initiator of MapReduce, Google has developed the Dremel system to shorten the processing time to the second level, as a strong complement to MapReduce. As a report engine for Google BigQuery, Dremel is very successful. Like MapReduce, Dremel also needs to run together with data and to move computing to data. It requires file systems such as GFS as the storage layer. Dremel supports a nested data model, similar to Javascript Object Notation (JSON). The traditional relational model inevitably has a large number of join operations in it: is often powerless when dealing with large-scale data. Dremel also uses column storage, so it only needs to scan the part of the data that is needed to reduce access to CPU and disks. Meanwhile, column storage is compression friendly; using compression can reduce storage space and achieve maximum efficiency.

Spark [42] is a real-time data analysis system developed by the AMP Lab at the University of California, Berkeley; it adopts an open-source cluster computing environment similar to Hadoop, but Spark is superior in the design and performance of task scheduling and workload optimization. Spark uses in-memory distributed datasets, in addition to providing interactive queries, and it can also optimize the workload of iterations [43]. Spark is implemented in Scala and uses it as the application programming framework, which can be tightly integrated. Scala can easily operate on distributed datasets as it does on local collection objects. Spark supports iterative operations on distributed datasets and is an effective complement to Hadoop, supporting fast data statistics analysis. It can also run concurrently on the Hadoop file system, supported by a third-party cluster framework named Mesos. Spark can be used to build large-scale, low-latency data analysis applications.

Impala [44], released by Cloudera recently, is similar to Google’s Dremel system. It is an effective tool for big data real-time queries. Impala can offer fast, interactive SQL queries on HDFS or HBase; besides a unified storage platform, it also uses Metastore and SQL syntax—the same as those used by Hive. It provides a unified platform for batch and real-time queries.

### 2.4.4.3 Streaming computing

In many real-time application scenarios, such as real-time trading systems, real-time fraud analysis, real-time ad delivery [45], real-time monitoring, or real-time
analysis of social networks, the data volume is large, the requirement for real-time response is high, and the data sources are continuous. New arrival data must be processed immediately or the subsequent data will pile up and the processing will never end. We often need a sub second or even sub millisecond response time, which requires a highly scalable streaming computing solution.

Stream Computing [46,47] is designed for real-time and continuous data, analyzing the movement process in real-time while the stream data is changing; capturing the information that may be useful to the users; and sending the result out. In the process, the data analysis and processing system is active, and the users are in a passive state of reception, as shown in Figure 2.5.

Traditional stream computing systems are generally based on an event mechanism, and the amount of data processed by them is small. The new stream processing technologies, such as Yahoo’s S4 [46,47], are mainly used to solve stream processing issues that have a high data rate and a large amount of data.

S4 is a general-purpose, distributed, scalable, partially fault-tolerant, pluggable platform. Developers can easily develop applications for unbounded, uninterrupted stream data processing on it. Data events are routed to processing elements (PEs); PEs consume these events and handle them as follows:

1. send out one or more events that may be processed by other PEs;
2. publish results.

S4’s design is primarily driven by data acquisitions and machine learning in a production environment on a large scale. Its main features include:

1. A simple programming interface to handle data streaming.
2. A high-availability cluster that is scalable on commodity hardware.
3. Use of local memory on every processing node to avoid disk I/O bottlenecks and to minimize latency.
4. Use of a decentralized, peer-to-peer architecture; all nodes provide the same functions and responsibilities with no central node to take special responsibility. This greatly simplifies deployment and maintenance.
5. Use of a pluggable architecture to keep the design as generic and customizable as possible.
6. A user-friendly design concept—that is, one that is easy to program and is flexible.

![Figure 2.5 Process of stream computing.](image-url)
There are many shared characteristics between S4’s design and IBM’s stream processing core SPC middleware [48]. Both systems are designed for large amounts of data. Both have the ability to use user-defined operations to collect information in continuous data streams. The main difference is in the structural design: SPC’s design is derived from the Publish/Subscribe mode, whereas S4’s design comes from a combination of the MapReduce and Actor models. Yahoo! believes that because of its P2P structure, S4’s design has achieved a very high degree of simplicity. All nodes in the cluster are identical; there is no central control.

SPC is a distributed stream processing middleware to support applications that extract information from large-scale data streams. SPC contains programming models and development environments to implement distributed, dynamic, scalable applications. Its programming models include APIs for declaring and creating processing units (PE), as well as a toolset for assembling, testing, debugging, and deploying applications. Unlike other stream processing middleware, in addition to supporting relational operators, it also supports nonrelational operators and user-defined functions.

Storm [49] is a real-time data processing framework similar to Hadoop and open sourced by Twitter. This kind of stream computing solution with high scalability and the capability of processing high-frequency and large-scale data can be applied to real-time searches, high-frequency trading, and social networks. Storm has three acting scopes:

1. Stream Processing
   Storm can be used to process new data in real time and to update a database; it has both fault tolerance and scalability.

2. Continuous Computation
   For this use, Storm is set up as a distributed function that waits for invocation messages. When it receives an invocation, it computes the query and sends back the results.

3. Distributed RPC
   Storm is also set up as a distributed function that waits for invocation messages. When it receives an invocation, it computes the query and sends back the results.

2.4.5 Data presentation and interaction

Computing results need to be presented in a simple and intuitive way, so users can understand and use them to form effective statistics, analyses, predictions, and decision-making processes to be applied to production practices and business operations. For this reason the display technology of big data, as well as technology for interacting with data, plays an important role in the big data picture.

Excel spreadsheets and graphics are data display methods that people have known and used for a long time; they are very convenient for everyday simple data applications. Many Wall Street traders still rely on Excel and years of accumulated and summarized formulae to carry out large stock trades. Microsoft and a number of entrepreneurs have seen the market potential and are developing big data
processing platforms that use Excel for presentation and interaction, and that integrate Hadoop and other technology.

The perception and processing speed of graphics by the human brain is far greater than that of texts. Therefore, presenting data by means of visualization can expose latent or complex patterns and relationships in data at a deeper level. With the rise of big data, there have emerged many novel means of data presentation and interaction, as well as start-up companies that focus on this area. These novel methods include interactive charts, which can be displayed on Web pages and support interactions, and which can operate and control icons, animations, and demos. Additionally, interactive map applications—such as Google Maps—can create dynamic markers, generate routes, and superimpose panoramic aerial maps. Due to its open API interfaces, it can be combined with many user maps and location-based service applications, for which it has gained extensive application. Google Chart Tools also offer a variety of flexible approaches to Web site data visualization. From simple line graphs, to geographic maps, to gauges (measuring instruments), to complex tree graphs, Google Chart Tools provide a large number of well-designed charting tools.

Tableau [50], a big data start-up company from Stanford, is becoming one of the most outstanding data analysis tools. Tableau combines data computing and aesthetic charts perfectly, as shown in Figure 2.6. Its program is easy to use: users can

![Figure 2.6 Visualization examples of Tableau.](image-url)
drag and drop large amounts of data onto a digital “canvas” and can create a variety of charts promptly. Tableau’s design and implementation philosophy is: the easier the manipulation of the data is on the page, the more thoroughly companies can understand whether their business decisions are right or wrong. Fast processing and easy sharing are other features of Tableau. In only a few seconds, a Tableau Server can publish an interactive control panel on the Internet. A user only needs a browser to filter and select data easily and to get a response to her questions, which will increase the user’s enthusiasm for using the data.

Another big data visualization start-up company—Visual.ly [51]—is known for its abundant infographics resources. It is a creation and sharing platform of infographics combined with social network. We live in an era of data acquisition and content creation. Visual.ly is the product of the data age: a brand-new visual infographics platform. Many users are willing to upload infographics to a Web site and then share it with others. Infographics will greatly stimulate visual expression performance and will promote mutual learning and discussion between users. It is not complicated to use Visual.ly to make infographics. It is an automated tool that makes the insertion of different types of data quick and easy, and it expresses the data with graphics.

In addition, 3D digital rendering technology has been applied widely in many areas, such as in digital cities, digital parks, modeling and simulations, and design and manufacturing, with highly intuitive operability. Modern AR technology applies virtual information to the real world via computer technologies: real environment and virtual objects are superimposed in the same picture or space in real time. Combining virtual 3D digital models and real-life scenarios provides a better sense of presence and interaction. With AR technology, users can interact with virtual objects, such as trying on virtual glasses or virtual clothes, or driving simulated aircrafts. In Germany, when engineering and technical personnel are conducting mechanical installation, maintenance, or tuning with a helmet-mounted monitor, the internal structures of the machine and its associated information and data can be fully presented, which was not possible before.

Modern motion-sensing technologies, such as Microsoft’s Kinect and Leap’s Leap Motion somatosensory controller, are capable of detecting and perceiving body movement and gestures, and then converting the actions into computer and system controls, freeing people from the constraints of keyboard, mouse, remote control, and other traditional interactive devices, and making users interact with computers and data directly with their bodies and gestures. This can create the super-cool action in the movie “Minority Report,” in which Tom Cruise moves data in the air. Even more advanced technology can give us experiences close to those in the movie “Avatar.”

Today’s hottest wearable technologies, such as Google glass, have combined big data technology, AR, and somatosensory technology organically. With the improvement of data and technologies, we can perceive the realities around us in real time. Through big data searching and computing, we can achieve real-time identification and data capture of the surrounding buildings, businesses, people, and objects, and can project them onto our retinas, which can help us in real time to work, shop, and relax at great convenience. Of course, the drawbacks of this new device and
technology are obvious. We are able to be monitored constantly: with privacy being encroached upon and violated at all times. In the future we may have to wear a mask before we go out.

### 2.4.6 Related work

The scale of big data brings great challenges to data storage management and data analysis, and data management mechanisms are evolving. Meng and other scholars [52] have analyzed the basic concepts of big data and have compared it with major applications of big data. They have also explained and analyzed the basic framework of big data processing and the affect of Cloud computing technology on data management and have summarized new challenges we face in the era of big data. Tao et al. [53] have described and analyzed related concepts and features of big data, and domestic and overseas development of big data technology, especially from the data mining perspective, and the challenges we face in the era of big data. Meanwhile, some scholars have pointed out that the real time and validity needs of data processing requires a technological change of conventional data processing techniques, starting with big data characteristics for developing technologies for big data collection, storage, management, processing, analysis, sharing, and visualization [54]. This work pays more attention to the analysis of big data characteristics and development trends, and as opposed to problems related to big data—discussed more thoroughly in the present text.

Compared with traditional data warehousing applications, big data analysis has large volumes of data, and complex queries and analysis. From the perspective of big data analysis and data warehouse architectural design, literature [55] has first listed several important features that a big data analysis platform needs. It then goes on to analyze and summarize current mainstream implementation platforms, such as parallel databases, MapReduce, and hybrid architectures of both, and points out their strengths and weaknesses. HadoopDB [56,57] is an attempt to combine the two architectures. Other scholars [58,59] discuss the competition and symbiotic relationship of RDBMS and MapReduce and analyze the challenges they encountered during development. They also point out that relational data management technology and nonrelational data management technology complement each other—in constant competition—and will find the right position within the new big data analysis ecosystem. In the study of NoSQL systems, researchers like Shen Derong [60] summarize the related research of NoSQL systems systematically, including architecture, data model, access method, index technique, transaction characteristics, system flexibility, dynamic load balancing, replication policy, data consistency policy, multilevel caching mechanisms based on flash, data processing policies based on MapReduce, and the new generation of data management systems. The papers aforementioned tend to introduce data storage for big data, analyze different storage policies, and detail their advantages and disadvantages, but they stop short of comprehensively presenting big data technologies, and do not address the synergy between different big data technologies. They also don’t consider the relationship between big data technology and Cloud computing.
Modern science in the twenty-first century brings tremendous challenges to scientific researchers. The scientific community is facing the “data deluge” problem [2] that comes from experimental data, analog data, sensor data, and satellite data. Data size and the complexity of scientific analysis and processing are growing exponentially. The Scientific Workflow Management System provides some necessary supports for scientific computing, such as data management, task dependencies, job scheduling and execution, and resource tracking. Workflow systems, such as Taverna [61], Kepler [62], Vistrails [63], Pegasus [64], Swift [39], and VIEW [65], have a wide range of applications in many fields, such as physics, astronomy, bioinformatics, neuroscience, earth science, and social science. Meanwhile, the development of scientific equipment and network computing has challenged the reliable workflow systems in terms of data size and application complexity. We have combined scientific workflow systems with Cloud platforms as a service [66] of Cloud computing, to deal with the growing amount of data and analysis complexity. A Cloud computing system with a large-scale data center resource pool and an on-demand resource allocation function can provide scientific workflow systems better services than the environments already mentioned, which enables the workflow systems to handle scientific questions at the PB level.

Summary

Big Data is the hot frontier of today’s information technology development. The Internet of Things, the Internet, and the rapid development of mobile communication networks have spawned big data problems and have created problems of speed, structure, volume, cost, value, security privacy, and interoperability. Traditional IT processing methods are impotent when faced with big data problems, because of their lack of scalability and efficiency. Big Data problems need to be solved by Cloud computing technology, while big data can also promote the practical use and implementation of Cloud computing technology. There is a complementary relationship between them. We focus on infrastructure support, data acquisition, data storage, data computing, data display, and interaction to describe several types of technology developed for big data, and then describe the challenges and opportunities of big data technology from a different angle from the scholars in the related fields. Big data technology is constantly growing with the surge of data volume and processing requirements, and it is affecting our daily habits and lifestyles.

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