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Migration from HPC-based Data Processing Systems to Cloud-computing based Data Mining Systems

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Abstract. **This paper reflects of experimental efforts in system structure design with brief review and considerations various system characteristics. The study reports our progress of how to migrate a system with either OLTP or OLAP and their simply combination, through HPC-oriented data processing system to HPC-enhanced, cloud-configured system for big data processing and data mining. The system is also equipped with IBM supported big data technology. The experimental system provides an insight into small-middle scaled system structure and implementations for research and/or teaching-purposed system platform for higher education.**

Keywords: **Computer system structure, high performance computing, big data, cloud computing, OLTP, OLAP**

I. INTRODUCTION

Since last decade, data has been generated exponentially. The generation is due to rapid development of computer and information sciences and technology. It is the cost and performance of computer systems, the network facilities with fast data transfer speeds, the digital technology for equipment and devices, the maturity of computing and computational methodologies, and the enormous successful applications that drives the explosion of data. The explosive data have several characteristics such as huge volume size, fast growth rate, and various structure and formats etc. These characteristics can be objectively touched or sensed in our daily life. They can be called explicit characteristics of data. Although most of the data have no values or short-term values, some data do have great values to people. There are two kinds of valuable data. These valuable data are called information data. They can be defined as the data which explicitly or implicitly contain valuable information to be extracted.

Some of information data can directly used to serve people while others can be utilized in application systems such as devices or equipment. For example customers' bank accounts and their transaction data, or CT image data from digitalized modality in hospitals or their reconstructed data for 3D visualization. The value of these information data can obviously be observed or sensed. These data have explicit information values. We hereby can call them explicit information data (EID. These data often need to be either pre- or post-processed. The series of the data processes is defined as data processing.

There exit another kinds of information data whose information are hidden and cannot be directly sensed. In order to find out their information value, people need to use special process with various methodologies or strategies to extract the information. The data can be hereby called implicit information data (IID) and the corresponding data process is called data mining [1-6], a processing conceptually similar to gold mining.

However, abstractly there exit similarity and non-similarity between data processing and data mining. First, both processes need data to be processed. Second they are related to each other. Many implicit information data need to be data processed before go to mining stage and many data mining procedures include data processing. Third, both data processing and data mining needs computing and computational technologies. Forth, both data processing and data mining requires strong background and knowledge associated with domain data in a specific application fields. However, there is a significant difference between them. The most obvious distinctness, in system engineering perspective view, in data processing the inputs are data and outputs are also data, while in data mining the inputs are data and outputs are extracted knowledge. The knowledge gives information (abstraction) to make decision. Therefore, precisely speaking, the data mining is defined as knowledge mining or knowledge discovery from data [1]. From this point of view there conceptually different from gold mining. Technically, data mining can be defined as the computational process for discovering knowledge patterns in data sets, so the extract information hidden in the dataset can be extracted transformed to knowledge bank. In other words, data mining is an important technical step required in knowledge discovery. It involves data acquisition, database management systems (DBMS), pre-processing-based data processing, computational

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modeling and inference considerations, metrics, algorithm complexity analysis, computational complexity analysis, statistics and informatics, post-processing based discovered structures, data visualization for human interpretation, and the knowledgebase management system (KBMS). Data mining is considered as a computational analysis step of the "knowledge discovery in databases" process, or KDD[4], which is an important component in KBMS. The data mining is originally a computer or computational science domain. Now its scope has been extended many fields and its major methods are at the intersection of artificial intelligence (AI), machine learning (ML), statistics, and database management systems (DBMS).[1]

In computing perspective view, the data processing and data mining sometimes share with the same computing platforms and similar computational strategies (such as programming and computing complexity analysis tools), although each of which has its own specific computing algorithms and methods. Therefore in many applications, the computer facility can be shared for both missions. In other words, both computational tasks can be performed on the same platform. This requires a computer system architect to design and implement a computing system with the considerations for both uses in order to reduce cost/performance rate.

This paper reports our computer system design with consideration of both uses. The system architecture design migrates from high-performance-computing-based data processing architecture to cloud-computing-powered data mining structure with considerations. We first start with a system design for On-Line Transaction Processing (OLTP), through On-line Analysis Processing and their combination, and high performance computing (HPC) [7] based system for data process system, and end with HPC-enhanced and could-computing virtualization powered system for big data [8] processing and data mining [1-6] with MapReduce [9-10] and Hadoop [11]features.

II. OVERVIEW OF OLTP AND OLAP

2.1 Online Transaction Processing (OLTP)

Traditional database systems are often built upon the relational database which accounts for the relationships between tables of data. Most of the systems utilize a computer configured as On-Line Transaction Processing (OLTP) structure. The structure is specially designed for online/offline applications with transaction processing. It is transaction-oriented system architecture. The core principle is the customer's raw data can be immediately transferred to a central system for processing and processed results are return back to customers in a very short time. Its characteristic is to quickly process input data and provide an answer immediately. Therefore the system is called a real-time system. The most important measure criteria for OLTP system is the performance of system real time response. It is defined as a period of time from the time of data entrance to the time of request response, operated by OLTP database engine. OLTP is primarily dedicated for a traditional relational database application, such as banking transactions.

OLTP can support a large number of concurrent users for customers' regular adding and modifying data. It reflects the ever-changing. It is often used to verify transactions of complex relational data and to make the best response for business servicing activities. OLTP structure provides technology support to day-to-day operations with the advantage of quick handle hundreds of transactions instantly. Currently most of information systems require fast and frequent updates of large dataset, which is of priority for a business enterprise to maintain or increase its competitiveness. That requirement can be met by an OLTP system. In addition, the OLTP can also process and analyze near-real-time customer data with acceptable load balances through its well-established data management system, hence increasing the flexibility of enterprise information architecture.

Due to the needs on querying or manipulating a large amount of data with complex and various structures during business data analysis and information extraction, the traditional relational database systems have been unable to fully meet such requirements. Unfortunately, the conventional OLTP lacks of sufficient capability to handle data processing, to process data analysis, and to provide decision making mechanism. The OLTP structure is not a good choose. In order to ensure a system structure can handle both data processing and mining using OLTP structure, we have to find alternative solution.

2.2 *Online Analysis Processing*

There exists another system structure which has been launched and widely used in business processing. It is called Online Analytical Processing (OLAP) is originally dedicated for data warehouse system. Its structure is particularly to support the complex of analysis operation. It is a decision support system to help professionals and managers make decision. It can flexibly and quickly process and analyze a big data volume based on specific requests and to provide intuitive and understandable results for decision making, so the top managers of executives can quickly understand the needs for next strategic actions.

OLAP structure shares multidimensional information. It has coexistence of online data access and analytical processing. Through the multiple possible observations of information, the analysis software in OLAP can fast, stably, consistently access acquire interactive data, which

allows to explore the data for policy or decision makers. Decision data is multidimensional data with contents.

OLAP is mainly used for to support sophisticated analysis operations and to provide straightforward results in warehouse based applications. OLAP-based system and warehouse database system are different systems but have complementary relationships. A general data warehouse is a foundation or sub-system of OLAP, while OLAP functions can be used to design a better warehouse system which is clustered to OLAP storage. OLAP can be classified into three types: relational OLAP (ROLAP) and multidimensional OLAP (MOLAP) and hybrid OLAP (HOLAP). The characteristics comparison of the OLTP and OLAP systems can be found in Table 1.

	OLTP	OLAP
User	operational level, group manager	Decision makers and senior manager or CEOs
Function	Daily operation	Analysis and decision needs
Database Design	Application oriented	Knowledge Subject-oriented
Data structure	2D and structured	Historical, classified, multidimensional, integrated and unstructured
Acquisition	Read/write tens records	Read/write millions records
Work Task	Simple transaction	Complicated query
User Number	thousands	Thousands of millions
Data size	100MB-GB	100GB-TB
Time Requirement	Real-Time	No restricted in time
Main Applications	Database	Data warehouse

III. SYSTEM ARCHITECTURE FOR STAND-ALONE OLTP AND OLAP

In the initial stage, we design a centralized system with two subsystems: an OLTP for data storage and processing and an OLAP for data analytical processing as backbone. Such coexistence architecture is used to study the pros and cons of both systems. The advantage of such system structure layout is they are independent each other. There communications go through and internal network. Such scheme has high reliability, security, and easy to be implemented and maintained. The major disadvantages is

Its main disadvantage is a waste of system resources. The computing nodes within each system cannot be directly connected. The computing resources (both hardware and software) of the systems cannot be shared. The overall system scalability is low, when one needs to scale the system capacity for large volume of data. Therefore, it is not suitable to big data environment, which is out of our original envisage. Yet that is sort of experience we should obtain from. The system architecture is illustrated in Figure 1.

IV. SYSTEM ARCHITECTURE FOR HYBRID OLTP AND OLAP

The above stand-along OLTP and OLAP can only satisfy our basic need. However, the resources are wasted. We consider combine these two structures together, while still retaining their features. Therefore, we design an hybrid OLTP-OLAP (hOLTAP). The system architecture merges the computer hardware including computing nodes and storage devices together. It seems like a cloud computing architecture without virtualization. In the system software configuration, the OLTP component is used for structured relational dataset, and OLAP component for unstructured data and post processing of data analysis. This way, we can either maintain the high performance of instant transactional data processing or knowledge-oriented information extraction. In order to enlarge the system capability, we propose to scale the hOLTAP architecture to distributed hLTAP system architecture using distributed computing technology. The computational nodes are centralized, while data storage systems are distributed. A special system component based on client-server agent machine is needed to manage the distributed resources and to allocate storage space and storage. We store relational data into OLTP-configured database and large un-structure data into OLAP-based data warehouse. The system architecture can be shown in Figure 2.

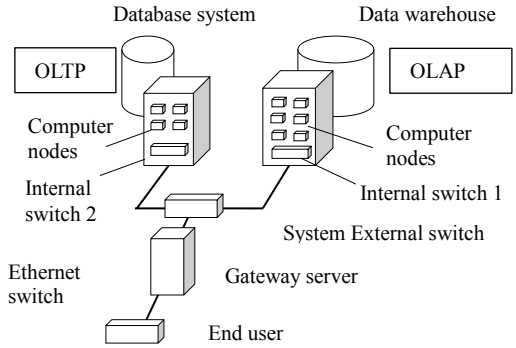


Figure 1. System architecture of stand-along OLPT and OLAP

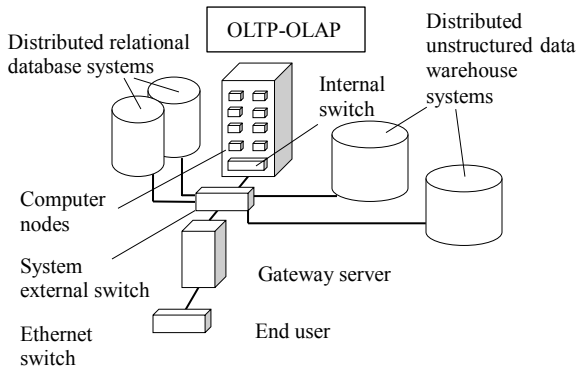


Figure 2. System architecture of hybrid OLPT-OLAP

V. PARALLEL COMPUTING-ENHANCED DATA TRANSACTION AND DATA PROCESSING

In OLTP-OLAP stand-along and hybrid OLTAP systems, loadings of computing nodes are quite different between transacting, or processing data. In order to increase the computational performance, we propose another approach in which the computation intensive tasks are accomplished through an internal parallel processing system, and regular data transaction and data processing used a small scale computing system. Therefore a parallel computing cluster is introduced to particularly handling intensive computing, while data management systems retain their data management capability and analysis functions. The computation intensive processing is handled by high performance computer cluster. In this proposed system, a high-speed data exchanger or switch is needed within the cluster. The cluster is managed by a cluster computing software system. High-performance data exchange across compute nodes take place in the cluster for intensive computation of data processing and analysis. Another high performance data switch is needed for data or file transfer among distributed database storage systems. The switch can also be connected to either local systems or through a gateway to external systems. The evolution of such clustering system architecture computing with special data processing and storage facilitates not only high performance computing-intensive data processing, but also data intensive computing and the data managements through well-matured database and warehouse management systems. The computer clustering technique with management and operation functions enables to integrate all types of distributed computing resources together to form a powerful cluster system.

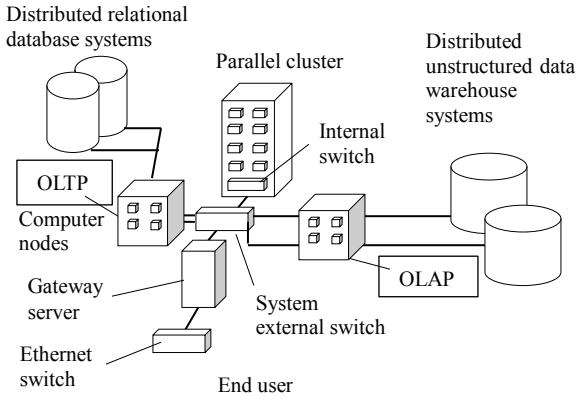


Figure 3. System architecture of parallel computing enhanced system with OLPT for relational data transaction and OLAP for unstructured data processing

This high performance computing (HPC) based system structure considers data processing efficiency using multi-process techniques. However, it does take into account the distributed data storages as well as huge data storage capacity. It also does not consider the distributed file systems configuration. In many enterprise data processing systems, the performances of parallel computing and data distribution, transferring and storage capacities in distributed environment should be considered at the same time. This leads us to rethink the architecture using the big data system architecture and technology to build our system. In the computing platform system design, we must first consider the main goal of the project: to enhance the performance of entire data processing, in terms of increasing processing speed or operational efficiency. We can model data processing system as a HPC system, while consider the distributed data storage system as required an auxiliary system for input/output data. The core of this structure is to design a system whose master or primary node manages pre-decomposed tasks to them distributed to all participated working nodes. Each working node conducts specified calculation and data exchange between nodes. Some dedicated nodes take care of data transfers from database management systems and storage devices to the cluster for computation and processing. During calculation, the distribution data stored in various data facilities are transferred to the parallel processing system for computation. This kind of system is suitable for scenario that data volume can be large but exchange rate is not high. It fits well to the case requests huge amount of data processes. Parallel computation of time compared with the time of data exchange is much large.

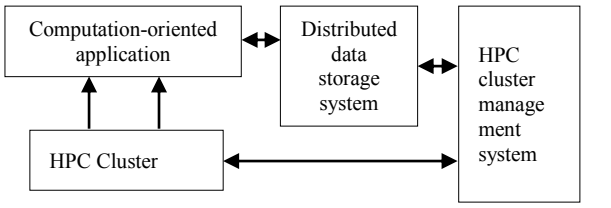
We can also model the data management system as main system, while consider the parallel computing system as a supplemental system to support its data processing. We can also model data processing and file processing together and consider a HPC just as an auxiliary computing system, when it is needed to manipulate data. There is no unique answer which model people should take. It is totally depends on specific application. In order words, there is no all-in-one all-purposed system architecture but has various variations.

Another situation is the task amounts of computations and data volume transfers are compromising each other. The data transfer and distribution are relatively frequently during computation or data processing. Data management activities also actively involve the whole data processing and analysis. In computational strategy, both data processing and data resources distribution should be considered. There is a need to overall leverage the balance between intensive data computations and frequent data volume access. IN such situation, we should consider use HPC approach with today's big data technology. In order to better

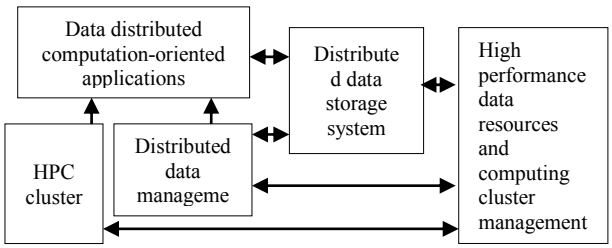
manage and utilize the available resources, the cutting-edge technology and services modes of cloud computing, especially successful virtualization technique should be employed. The combinations of scalable (may be perhaps distributed) HPC system, cloud, and big data enable us to enlarge the overall computing facilities and services with high flexibility and scalability facilities and richen the computational algorithms with parallel features, as well improve high performance distributed data or file processing with big data strategy. The integration of these three needs system engineering powered integrated system architecture and technical implements skills by using today's matured computing cluster management system.

VI. HPC-ENHANCED CLOUD-BASED BIG DATA PROCESSING AND MINING SYSTEM ARCHITECTURE

The system structure for high performance computing is CPU intensive computation, while a process of large amount of data needs to handle data acquisition, distribution and transfers, management, and processing. It is data-oriented intensive computing. Therefore the system structure design and architectures are different. The major difference between two systems can be typically illustrated in Figure 4.



(a) HPC-based data processing system architecture



(b) Big-data-oriented data processing system architecture

Figure 4. System architecture difference between HPC-based data processing system and Big data-oriented data processing system

After experimenting above-mentioned systems test-bed configurations, we make substantive changes to design a system structure with main schema modifications. The system hardware equipment consists of three subsystems: data storage subsystem, high performance computing subsystem, and a cluster of servers.

The data storage subsystem is equipped with a disk arrays such as Redundant Arrays of Independent Disks (RAID). The data storage subsystem implements different software to support database and data storage. The relational database management systems with both the Oracle-Database 12c and IBM-DB2 are supported. Regarding unstructured data in distributed data files, we use the core component of big data software architecture, Hadoop Distributed File System (HDFS). Therefore, the data storage subsystem can break down a series of big task of processing data from distributed storage into smaller task pieces before distributing them to throughout the nodes in the HPC cluster. Each node invokes map and reduce functions execute on the smaller task for the subsets of your larger data sets; hence to provide the overall computational scalability for big data processing. All the subsystems are connected internally with an InfiniBand fast performance and intelligent switcher which operates data exchange among participated computer nodes. The international switch does not involve any external activities. It is only dedicated to improve the efficiencies computation and internal data transfers. In order to communicate externally, a GigBit Ethernet switch is used to facilitate the external connections for data exchange as well. This way, we can simulate OLTP and OLAP systems for relational data transfer and for data analysis and knowledge discovery. Simultaneous connections are necessary for peripheral development and network security systems, as well as for client-server-based computers.

In the HPC subsystem, a master node classifies big computational task into small ones, allocates computational resources and nodes, and distributes smaller task on each available compute (working) nodes

The cluster of servers is designed to provide accessible computing subsystem for various application services, mainly including network, data sharing, network security gateway, external data transfer gateway, special peripheral data acquisition, data achieve and backup, data visualization with a NVIDIA Tesla K20 GPU, and other possible services on demands.

Based on this paradigm, our HPC-enhanced, cloud-based big data processing and mining system is proposed hereby and shown in Figure 5.

VII. SYSTEM IMPLEMENTATIONS

The system configuration flexibility is required in order to experiment various system architectures. The flexibility of the system is measured based on system's reconfiguration, scalability, and applicability. The basic core technical measures include

- Distributed File Storage
- Multiple HP Inner Networks
- Cloud Virtualization and Parallel Computing
- Heterogeneous Clustering Management
- MapReduce, Hadoop, HDFS capability for big data applications
- Data processing, statistical analysis and certain data mining functions

The proposed system is technically implemented using IBM Flex systems x240. The system chassis has 10 blades. The system installs IMB Flex system hardware has 108*CPU cores of 2*E5-2620, total 320 GB memory and 15 TB disk space with RAID technology. The internal networks within the system have two high performance data exchange switchers. One is the 56GB Infiniband intelligent switcher and another is 1GB Ethernet switchers. The operating system uses Redhat Enterprise Linux 6.3. We select 9 compute physical nodes as a manager node and hypervisor computer nodes, respectively. The master node takes care of overall system performance and management of all the participated computer nodes. The hypervisor nodes are performing intensive computation tasks. The cluster computer subsystems and computer nodes is managed by the IBM PCMAE, new version of IBM Platform. The cloud virtualization is configured using IBM Platform Symphony, as middleware for resources virtualization. The shared data storage, data transfer, and management is facilitated by IBM General Parallel File System (GPFS), a high-performance enterprise file management system, which enables manager and transfer distributed data with optimizing features. Two physical computer nodes are dedicated the operation of GPFS and HDFS respectively. Each node is virtually configured with 16 virtual computing nodes by IBM Platform Symphony software. Another physical computer node is equipped with Hadoop and configured as 16 virtual computer nodes for Hadoop-supported MapReduce computations for simulating a distributed big data processing. The physical computing resources or nodes are managed can visualized by xCat built in IBM PCMAE and virtual computing resources or virtual nodes are managed and visualized by IBM Platform Symphony.

For data intensive computing, the system employs big data technologies using MapReduce methodology[9-10], Hadoop Distributed File System (HDFS) and other Hadoop fesures. For data analysis and data mining, the system installs IBM SPSS and other customized software. Regarding HPC and parallel computing subsystem, the system installs message passing interface (MPI) to handle parallel computing by passing data and commands among computational nodes.

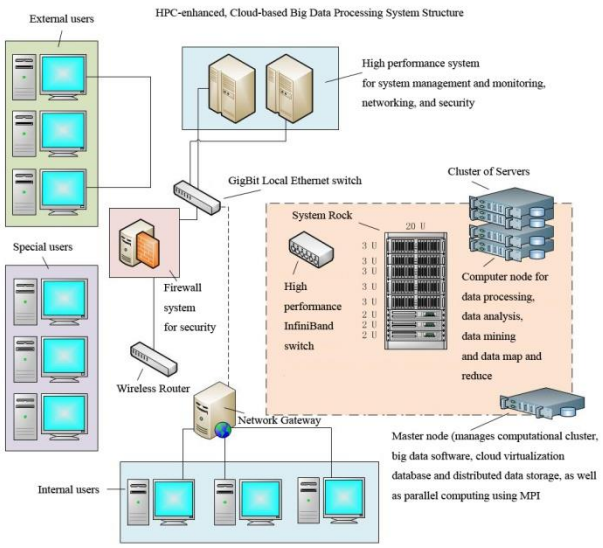


Figure 5. HPC-enhanced, Cloud-based cluster for dig data processing and data mining

According to our predefined project goal of developing an infrastructure to enhance an institutional research and teaching in data science and engineering, the experiment system provides a platform test-bed. In order to fully utilize all computing resources, we implement the system with cloud virtualization technology to dynamically manage all the participated computing resources, while remains the system structure unchanged.

VIII. CONCLUSION

This paper reports our system structure design strategy and considerations. It starts with a simple combination of stand-along OLTP and OLAP. It migrates to hybrid one with their system integrations. In order to consider the increase computational performance, a high performance computing system is included therein. However it cannot meet with the requirement for handling large-scale distributed data processing, especially unstructured data stored in a distributed environment. After reviewing all the systems characteristics, we end with the system architecture of HPC-enhanced and cloud-based big data processing. The system fully integrates all the high-end technologies together to meet our needs in bother data intensive computing and CPU intensive computing, especially for big data processing and data mining. The future work will be planned to add knowledge bank for data mining outputs.

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