Odysseus/DFS: Integration of DBMS and Distributed File System for Transaction Processing of Big Data

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Abstract

The relational DBMS (RDBMS) has been widely used since it supports various high-level functionalities such as SQL, schemas, indexes, and transactions that do not exist in the O/S file system. But, a recent advent of big data technology facilitates development of new systems that sacrifice the DBMS functionality in order to efficiently manage large-scale data. Those so-called NoSQL systems use a distributed file system, which support scalability and reliability. They support scalability of the system by storing data into a large number of low-cost commodity hardware and support reliability by storing the data in replica. However, they have a drawback that they do not adequately support high-level DBMS functionality. In this paper, we propose an architecture of a DBMS that uses the DFS as storage. With this novel architecture, the DBMS is capable of supporting scalability and reliability of the DFS as well as high-level functionality of DBMS. Thus, a DBMS can utilize a virtually unlimited storage space provided by the DFS, rendering it to be suitable for big data analytics. As part of the architecture of the DBMS, we propose the notion of the meta DFS file, which allows the DBMS to use the DFS as the storage, and an efficient transaction management method including recovery and concurrency control. We implement this architecture in Odysseus/DFS, an integration of the Odysseus relational DBMS [35], that has been being developed at KAIST for over 24 years, with the DFS. Our experiments on transaction processing show that, due to the high-level functionality of Odysseus/DFS, it outperforms Hbase, which is a representative open-source NoSQL system. We also show that, compared with an RDBMS with local storage, the performance of Odysseus/DFS is comparable or marginally degraded, showing that the overhead of Odysseus/DFS for supporting scalability by using the DFS as the storage is not significant.
1 Introduction

1.1 Necessities of Large-Scale Data Management

The relational database management system (RDBMS) has been widely used as an optimal solution to systemically manage structured data for decades [27]. The RDBMS provides improved productivity for both producers and users of the application programs. Specifically, compared to the low-level functionalities of the O/S file system, the RDBMS supports various high-level functionalities such as data types, schemas, transactions, indexes, and SQL.

Rapid advancement of computing systems and computer networks facilitated numerous services and applications that did not exist before, and the necessity for managing large-scale data has naturally emerged during this process [15]. Explosive growth of large-scale digital data from social media, Web, sensors, and other data sources made it impossible to manage them efficiently by simply extending the current computing paradigm. The term big data was coined to cope with such problems of explosive inflation of data, which need to be solved as a new area of computing [11]. In practice, it was reported that the digital information content of the world amounted to 1.8 zettabytes\(^1\) in 2011 and was to increase by tens to hundreds of times in ten years [15]. It was reported that Facebook currently manages over 140 billion photos, and more than 7 billion photos are uploaded each month [3]. It means that a single Internet service manages data over 100 petabytes, assuming the size of a photo is about one megabyte.

1.2 Techniques for Large-Scale Data Management

As the amount of data that computer systems need to manage increases, a number of techniques for managing large-scale data were developed [1, 2, 24, 25, 30, 31]. They can be classified into three categories according to the way the system is configured.

First, the most basic way is to configure a single node RDBMS with a massive storage device. In this method, we implement an RDBMS on a high-performance single machine that can handle a large

\(^1\)Zettabytes are a million petabytes.
number of queries and manage large-scale data using massive storage devices such as a disk array or a SAN. Generally, this method is widely used in small-scale companies with small-sized data to manage and has an advantage that the system configuration is relatively easy. However, there are physical limitations in configuring beyond a certain level of storage capacity or providing services beyond a certain level of transaction loads in a single machine. Capital burden is also a problem since the price of the massive storage hardware is very expensive and guaranteeing high level fault-tolerance at the hardware level is also very expensive.

Second, we can use a distributed/parallel DBMS that distributes data and processes queries over multiple nodes [28]. This configuration extends capacities of data storage and query processing by storing data over multiple nodes and processing queries in parallel. But, the distributed/parallel DBMS has several drawbacks [2]. (1) System configuration is complex, (2) software of a distributed/parallel DBMS is expensive, (3) as the number of nodes increases more than several tens of nodes, the inter-node communication overhead increases exponentially, (4) the architecture has an operability problem caused by decrease of mean-time-before-failure of the system due to failure of individual nodes. So, this architecture is difficult to scale beyond a certain number of nodes.

Third, we can use NoSQL systems. By storing large-scale data in a distributed file system and processing them in parallel using more than thousands of commodity machines, NoSQL systems make up for the drawbacks of the two former architectures [25]. NoSQL systems such as GFS or Hadoop DFS (HDFS) utilize a number of machines connected through a network and support scalability, reliability, and availability. Building a large-scale storage using NoSQL systems is widely accepted for big data management since its cost is several times less than that of using a single-node RDBMS with a disk array or using a distributed/parallel DBMS [18].

1.3 Motivation

The distributed file system (DFS) and key-value store are representative examples of NoSQL systems. The DFS is designed to store large-scale data on a distributed network that consists of a huge number
of commodity hardwares. It stores data by the unit of a large block distributed over those machines [16]. The DFS supports scalability by adding any number of new nodes and fault-tolerance by maintaining multiple replicas of data blocks. The key-value store is a storage system for storing a table-like structure by the unit of <key, value> pair [8]. The key-value store supports scalability and fault-tolerance by using the DFS as the storage.

On the other hand, NoSQL systems have disadvantages of lacking high-level DBMS functionalities compared to the RDBMS [1]. That is, NoSQL systems are designed to support scalability for large-scale systems by limiting certain DBMS functionality [10, 16]. Figure 1 compares functionalities of the RDBMS to those of the NoSQL systems using the key-value store.

| Systems                        | Relational DBMS                                   | NoSQL systems with Key-value store |
|--------------------------------|--------------------------------------------------|-----------------------------------|
| Storage structure              | Row store (traditional), column store             | Row store among blocks            |
|                                |                                                  | Column store within a block       |
| Query interface                | SQL                                              | Storage system API                |
| Data type                      | Integer, Float, String, Varstring                | Varstring                         |
| Join, Aggregation              | Supported                                        | Not supported*                    |
| Transaction                    | Supported                                        | Supported (only single row transactions) |
| Schema                         | Predefined schema (Expensive to modify)          | Schema by using both row and column key (Cheap to modify) |
| Indexing                       | Supported                                        | Supported only for the row key (primary index) |

* Since the key-value store can have any number of columns, data are commonly stored in a denormalized structure (i.e., already joined). Thus, the join operation is not absolutely necessary and is not supported. On the other hand, the key-value store suffers from redundancies incurred by the denormalized data structure.

There have been a lot of effort to support high-level DBMS functionality in a NoSQL system [2, 23, 26, 29]. However, most of those efforts just add some DBMS functionality to NoSQL systems rather than supporting full DBMS functionality. We discuss these works in more detail in Section 2.3.

1.4 Our Contributions

In this paper, we propose a new DBMS architecture that can efficiently manage large scale big data with full DBMS functionality. We make the following four major contributions: First, we propose a new
architecture, \textit{Odysseus/DFS}, that integrates the RDBMS with the DFS. Effectively, it is an RDBMS that uses the DFS as the storage system. Thus, it supports scalability and fault-tolerance of the DFS and provides high-level functionalities of the RDBMS.

Second, we propose the notion of the \textit{meta DFS file}, which allows the RDBMS to use the DFS as the storage. The DFS is a write-once-read-many storage that do not allow in-place overwriting and appending. Our storage manager solves those problems using the notion of the meta DFS file. The storage manager also performs mapping between a DFS block and DBMS pages.

Third, we propose an efficient transaction management method including concurrency control and recovery when using the DFS as the storage. Our method supports schedules serial with respect to write transactions but concurrent with respect to read transactions. It supports coarse-granularity locking in order to minimize the locking overhead in a distributed environment. We note that the general architecture of Odysseus/DFS is RDBMS-independent. Our storage management and transaction management methods can be easily adapted to any RDBMS that uses the page as the unit of I/O.

Last, we show by experiments that, in terms of performance, Odysseus/DFS outperforms Hbase and is comparable to or marginally degraded from the RDBMS. These results are very promising in that our methods have a more complete DBMS functionality compared to Hbase, and yet, have better scalability and fault-tolerance compared to RDBMS.

The rest of this paper is organized as follows. In Section 2 we review the representative platforms for big data management. In Section 3 we present our new system, Odysseus/DFS. In Section 4 we present the recovery methods for Odysseus/DFS. In Section 5 we discuss how we implement locks for Odysseus/DFS. In Section 6 we present the performance of Odysseus/DFS compared to other data management systems. Finally, in Section 7 we conclude the paper.
2 Related Work

In this section, we review related work that are used for large-scale data. Section 2.1 reviews recent research efforts on improving scalability of parallel DBMSs. Section 2.2 covers NoSQL systems and recent advances on them. Section 2.3 reviews research efforts on providing NoSQL systems with high-level DBMS functionality.

2.1 Parallel DBMSs

There have been some research efforts on improving scalability of the parallel DBMS to the level of NoSQL systems by carefully limiting certain functionalities of the DBMS. Commercial parallel DBMSs for big data analytics such as Teradata, GreenPlum, Sybase, and Vertica have shared-nothing MPP architectures. Thus, these systems improve scalability by adding multiple machines to the network where dependencies among nodes are minimized. However, they do not take advantage of NoSQL system features such as scalability, fault-tolerance, and load-balancing.

There are some research works that support limited DBMS functionality optimized for handling a specific target workload in the DBMS. PNUTS by Yahoo! supports scalability with eventual consistency. Eventual consistency relaxes the consistency level compared to strong consistency usually supported by the DBMS. ODYS by KAIST shows that a large-scale search engine can be constructed by a shared-nothing massively-parallel configuration of the DBMS using tight integration of DB and IR features.

2.2 NoSQL Systems

NoSQL systems are designed to easily add new machines for scalability and to support load balancing among heterogeneous machines. In addition, they support fault-tolerance by replicating data into multiple nodes.

The components of typical NoSQL systems can be classified into four layers with respect to their functions: (1) the storage layer, (2) key-value store layer, (3) parallel execution layer, and (4)
language layer. The storage layer provides the DFS. Representative systems include GFS [16] and HDFS [20]. The key-value store layer provides management of data stored in the DFS in a key-value pair format. Representative systems include BigTable [8] and Hbase [19]. The parallel execution layer provides systems for processing queries in parallel. The representative systems are MapReduce [11] and its open-source version Hadoop. It splits a job to multiple tasks, assigns them to nodes, and processes them in parallel. The language layer provides translation from a query written in a higher-level language like SQL to a MapReduce job. Representative systems include Pig [23] and Hive [29]. A distributed lock manager, which manages shared resources in a distributed environment is also a primary component of a NoSQL system although it cannot be classified into the above four layers. Representative systems include Chubby [7] and Zookeeper [36].

Figure 2 represents an evolutionary path of data management systems. The RDBMS has been widely used due to its rich functionality compared to an O/S file system, but it has limitations in dealing with large-scale data. Therefore, to overcome the limited scalability of the RDBMS, NoSQL systems have been proposed emphasizing scalability and fault-tolerance. The drawback of these systems, however, is that they lack the rich functionality of the DBMS. Finally, the new class of systems (the end of the arrow of Figure 2), which supports both scalability and DBMS-level functionality, has become an issue in the literature [1]. Section 2.3 describes these new systems.

Figure 2: Evolution of data management systems.
2.3 Supporting DBMS Functionality on NoSQL Systems

In this paper, we classify efforts to support DBMS functionality on NoSQL systems into two categories: (1) those on top of the parallel execution layer [21, 23, 29] and (2) those below the parallel execution layer [2, 5, 12, 13, 26].

2.3.1 Supporting DBMS Functionality on Top of the Parallel Execution Layer

Most efforts have implemented a higher-level language layer on top of the parallel execution layer [1]. Although MapReduce allows us to easily execute parallel programs, programming in MapReduce is still a burden. Thus, in order to provide a more convenient programming environment, several methods have been proposed for managing parallel tasks in MapReduce using a higher-level language such as SQL. Specifically, these techniques transform a user query into an equivalent MapReduce job and return the results obtained by MapReduce to the user. The representative systems are Hive [29] and Pig [23]. They belong to the language layer of Section 2.2. Besides high-level languages, methods of processing join operations using MapReduce have also been studied [4].

2.3.2 Supporting DBMS Functionality below the Parallel Execution Layer

HadoopDB [2] directly utilizes the RDBMS to process MapReduce tasks. HadoopDB uses the RDBMS to process SQL queries for data analysis. That is, when processing analytic tasks, HadoopDB first bulk-loads a segment of the DFS data to the local database of each slave node and uses the local DBMS of the node to process the data loaded in the node. Parallel coordination is performed by MapReduce in the master node. Since DBMS accesses the local data temporarily stored in a node, HadoopDB suffers from duplicated storage. It also has performance overheads due to loading DFS data to local databases.

Hadoop++ and HAIL support DBMS schemas and indexes in the DFS using API functions provided by the DFS and MapReduce library [12, 13]. Especially, HAIL supports multiple clustering indexes by clustering differently each replica of the DFS. However, they do not support a higher-level language such as SQL.
Brantner et al. \cite{5} has proposed a storage system that supports transactions on top of Amazon’s S3 system\footnote{a distributed file system for Amazon cloud services}. It also proposes methods of implementing various target consistencies in Amazon S3. But, it lacks other DBMS functionalities such as the query language and indexes.

The F1 DBMS \cite{26} by Google supports some DBMS functionalities such as SQL and transactions on top of the key-value store. Since F1 uses the key-value store, it can manage large-scale data with scalability and fault-tolerance. The F1 DBMS is similar to Odysseus/DFS proposed in this paper in that both systems have been designed to support scalability and full features of a DBMS. F1 has some DBMS functionalities such as multi-version transaction processing, secondary indexes, and SQL. It also supports other features that satisfy requirements of the AdWords business of Google.

However, F1\cite{26} seems to have the following limitations. First, F1 uses a key-value store rather than a relational store. While a key-value store has the disadvantage of redundantly representing the data, it is not clear how F1 makes up for this disadvantage. Second, F1 proposes the concept of the hierarchical schema through a series of one-to-many relationships. The hierarchical schema stores tuples that are pre-joined from multiple relations in the physical storage. As a result, it cannot support an efficient sequential scan of a relation for on the one-side of the one-to-many relationship since tuples in the relation are interleaved with those in their descendant relations. Furthermore, it is not clear whether it can also efficiently support other complex schemas involving many-to-many relationships. These limitations are contrasted with Odysseus/DFS, which is designed to integrate a full-blown RDBMS with the DFS.

3 Odysseus/DFS

3.1 The Architecture

Figure \ref{fig:architecture} depicts the architecture of Odysseus/DFS. Odysseus/DFS is composed of one master node, multiple DBMS server nodes, and multiple DFS slave nodes. The master node plays the roles of a DFS\footnote{Names of components of the DFS are from those of HDFS \cite{20}}.
NameNode and Distributed Lock Manager. The DFS slave nodes contain DFS DataNodes. A DBMS server node consists of a DBMS server, Meta DFS File Manager, DFS Transaction Manager, and DFS Client. A DBMS application residing in a DBMS client node accesses DBMS servers in the DBMS server nodes through a DBMS Client. The nodes described in the figure can be arbitrarily deployed. For example, we can deploy DFS DataNode, DBMS client/server, and DBMS application in the same machine or each of them in a different machine. A DBMS server accesses data in the DFS through the Meta DFS File Manager and manages transactions through the DFS Transaction Manager.

The DFS NameNode manages the metadata of DFS files. A DFS DataNode stores partitions of DFS files in duplicates. A DFS Client provides the user interface necessary for using the DFS. The Distributed Lock Manager manages locks for concurrency control. A Meta DFS File Manager manages meta DFS files. A meta DFS file is a collection of DFS blocks and supports in-place overwriting and appending operations in the unit of a DFS block. The roles of the Meta DFS File Manager are explained in Section 3.3 in detail. The DFS Transaction Manager performs data update, recovery, and concurrency control so as to satisfy ACID properties of the transactions in using the DFS as storage. They are elaborated in Sections 4 and 5 in detail.

Figure 3: The architecture of Odysseus/DFS.
The architecture of Odysseus/DFS is novel and different from other existing architectures proposed to manage large-scale data. The architectural difference between Odysseus/DFS and other systems are summarized below:

- **Single node RDBMS:** The RDBMS uses local disks, a disk array, or a SAN as its storage while Odysseus/DFS uses the DFS. Therefore, Odysseus/DFS takes advantage of the DFS such as fault-tolerance, load balancing, and scalability while the RDBMS cannot.

- **Parallel DBMS (PDBMS):** (1) Since, like in the RDBMS, the PDBMS stores data in local disks, a disk array, or a SAN of slave nodes, it cannot take advantage of the DFS. (2) Since the PDBMS partitions the entire data into slaves in a shared-nothing manner, each slave of the PDBMS cannot directly access the data stored in the other nodes. Thus, the ‘explicit’ communication among multiple different DBMSs in the slaves is incurred. In contrast, since a DBMS server of Odysseus/DFS accesses data through the DFS, it can access any data stored in the other nodes by the ‘implicit’ communication conducted by the DFS, providing the view of an integrated DBMS. (3) The PDBMS does not know the place where the data necessary for processing a query reside. Thus, to process a query, the PDBMS uses repartitioning or broadcasting, which incur an excessive communication cost or uses semi-join like methods, which need pre-processing. In contrast, a DBMS server of Odysseus/DFS can exactly locate data necessary for processing the query through the DFS by using the physical page identifier provided by the DBMS—reducing the communication cost compared with the PDBMS.

- **Key-value store:** (1) The key-value store provides only basic functions for data management on the data represented in the key-value format while not providing full functionality of the DBMS. (2) Since, like the PDBMS, the key-value store stores data in multiple slave nodes in a shared-nothing manner, each slave node cannot directly access the data stored in the other nodes.

- **Language layer system:** Systems such as Pig or Hive have a language layer, whose primary goal is to support a high-level language for big data analytics on top of the MapReduce framework. Since these systems primarily support queries and workloads for analytics, they do not support other DBMS functionalities (e.g., transaction processing).
• Google F1 DBMS: Google F1 DBMS introduces a module for supporting SQL and transaction processing on top of a key-value store (i.e., BigTable) based on the DFS. In contrast, in Odysseus/DFS, the RDBMS is integrated directly on top of the DFS. To implement full DBMS functionality, F1 should completely re-implement a new query processor that can use a key-value store as the storage. In contrast, the architecture of Odysseus/DFS is RDBMS-independent. Hence, the Odysseus/DFS approach allows us to use an existing RDBMS that already has full DBMS functionality by adopting our Meta DFS File Manager and DFS Transaction Manager, minimizing implementation overhead.

3.2 Characteristics of the DFS

The DFS is a system storing data by managing local storages of multiple machines connected through a network. A DFS file is partitioned and stored by the unit of the DFS block. A DFS block is replicated in multiple distinct DFS DataNodes for fault tolerance. The DFS NameNode manages metadata describing the mapping between the DFS file and DFS blocks that are stored in DataNodes and periodically checks health of each DataNode to avoid data loss.

The DFS Client provides API functions for applications and communicates with the NameNode and DataNodes. The DFS Client supports the following four types of API functions: reading, writing, renaming, and deleting a particular DFS file. The DFS has the following characteristics in reading/writing data.

• The DFS Client supports random reads in the unit of the byte. Random reads in the DFS, however, are slower than those in a local disk. While, in processing a random read, a local disk incurs latency corresponding to the disk access time, the DFS incurs additional overhead of (1) metadata lookup from a DFS DataNode and (2) network transfer when data are transmitted through the network. We call this overhead the network transfer overhead. When we read from or

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4In some documents, the term ‘chunk’ is used. In this paper, we use the term ‘DFS block’ consistently. The DFS block size is configurable (64MB by default).

5The number of replicas of a DFS block is also configurable (3 by default).
write into a large-sized DFS file, the network transfer overhead in the DFS is relatively negligible since network transfer can be done in parallel with disk read/write.

- When we sequentially read from or write into a large-sized DFS file in another node, if the network speed is slower than the disk transfer rate, network speed becomes a bottleneck. We call this overhead the network bottleneck overhead.

- The DFS Client does not support API functions for in-place overwriting or appending to an existing DFS file. Hence, the DFS is called a write-once-read-many storage. If we have to overwrite in-place or append to the DFS file, we should perform the following process that incur a very high overhead. First, we read the target DFS file and store and modify it in a temporary storage. Next, we delete the existing DFS file and write a new DFS file that has same file name as the old one with the modified content. In this paper, we call this process a DFS file remake.

### 3.3 Meta DFS File Manager

We introduce an abstract data type, which we call the *meta DFS file*, to manage the DFS file effectively. For supporting updates to the database, the RDBMS must be able to overwrite or append data to an arbitrary position within the database. However, the DFS does not support in-place overwrite and append operations as described in Section 3.2. The meta DFS file supports not only read and write operations that are supported by the DFS API, but also in-place overwrite and append operations. To support these operations, the meta DFS file partitions data into multiple DFS files, where each DFS file consists of one DFS block. Thus, a meta DFS file is as an ordered set of DFS files.

Figure 4 illustrates the architecture of the Meta DFS File Manager that manages meta DFS files. The Meta DFS File Manager accepts and processes a read, overwrite, and append request to a particular meta DFS file from the DBMS server. A meta DFS file maintains an ordered set of DFS files that belongs to it. To maintain an ordered set, Meta DFS File Manager names each DFS file as a concatenation of the meta DFS file name and \textit{block id} of the DFS file. For example, to store the meta DFS file $(PATH)/data/
of size 256MB, Meta DFS File Manager manages it as four DFS files of size 64MB and names each DFS file as $(PATH)/data/00, $(PATH)/data/01, $(PATH)/data/02, and $(PATH)/data/03, respectively. The DFS NameNode maintains the Meta DFS File Table for managing the DFS files that belong to each meta DFS file. The attributes of Meta DFS File Table are DFS file name, file size, the number of blocks, the number of replicas, and the block position of each DFS block. The block position stores as many DataNode IDs as the number of replicas.

![Diagram of Meta DFS File Manager](image)

Figure 4: The architecture of the Meta DFS File Manager.

We also need to resolve syntactic differences between the DBMS page and the DFS block. We sequentially assign the pageid to each page in a DFS block to map the address space of the database to that of the meta DFS file. As a result, we can easily obtain the block_id and page_offset of a page in a DFS block by a simple arithmetic operation. Specifically, block_id is $(pageid/N)$ and page_offset is $(pageid \mod N)$, where $N$ denotes the number of pages in a DFS block.

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7The mapping is ‘static’ since this mapping is between address spaces and not between the data and address space. Thus, obviously, any update of data does not influence the mapping itself.
4 Recovery

The recovery method we propose in this paper assumes that only one DBMS transaction can update the database at a time. In other words, the method assumes a serial schedule among write transactions and a concurrent schedule among read transactions. In the case where multiple processes reside in a single machine, we can easily implement locks in the O/S shared memory so that we can efficiently support locking. In the case where multiple processes reside in multiple machines as in the DFS, however, there is no efficient shared data structure such as the shared memory at the O/S level. Thus, we need an auxiliary system for synchronization among processes in multiple machines. We use Zookeeper [36] for this purpose. Zookeeper allows DBMS processes to synchronize with one another by providing remote API functions to create, access, and modify shared data structures. The details of implementation will be presented in Section 5. Since the interprocess communication through Zookeeper is much slower than through O/S shared memory, the performance of concurrency control could degrade severely. Therefore, using a large lock granularity is preferred to reduce the locking overhead. In this paper, we employ the database lock as the lock granularity.

Recovery methods based on immediate update such as ARIES [22] incur high locking overhead while guaranteeing high write-intensive concurrency. On the other hand, recovery methods based on deferred-update or shadow-pages incur low locking overhead [33]. Therefore, we employ a recovery method based on the latter as the recovery method for Odysseus/DFS.

The shadow-page deferred-update (simply, SPDU) method [33] combines the two methods to make up for the drawbacks of each method. In Section 4.1, we describe the SPDU recovery method in detail. In Section 4.2 we propose SPDU/DFS that modifies the SPDU method to resolve inefficiency when we apply it to Odysseus/DFS.

4.1 The SPDU Method

The deferred-update method [14] defers updates to a data page until commit time. Pages updated during a transaction are temporarily stored in a deferred update file. At commit time, updated pages are copied
into the original page locations of the database. This method has an advantage of maintaining clustering of the data regardless of repetitive updates in the data since it copies the updated pages back to the original page location of the database. On the other hand, it has a disadvantage of having difficulty in maintaining consistency in reading the database, which can be resolved only by reading both the database and the deferred update file during query processing.

The shadow-page method \(^{[17]}\) maintains the mapping between the logical and physical pageid’s using a page mapping table. Any page updated during a transaction is allocated a new page in the database. The method maintains both the new mapping table that reflects updates and the old one that does not. The method simply selects the new mapping table at commit but the old one at abort. The method does not incur the data inconsistency problem of the deferred-update method. On the other hand, when a page is updated, the method stores the updated page into a place different from the original one. Hence, repetitive updates in the data cause the clustering of the data destroyed.

The Shadow-Page Deferred-Update (SPDU) method \(^{[33]}\) hybridizes the deferred-update and the shadow-page methods. Hence, it has advantages of both methods. The SPDU method works correctly for a serial schedule with respect to write transactions and a concurrent schedule with respect to read transactions. Specifically, we store a database in a data file and store updated pages of the database in a log file, which is separate from the data file. Since a transaction deals with a database, a DBMS process for each transaction manages a data file and the corresponding log file. Whenever a DBMS process commits a transaction, the log file is reflected into the corresponding data file, and then, the log file is initialized. Thus, the log file allows to defer updating the data file, which plays the role of a deferred update file in the deferred-update method.

The deferred update method has the overhead of accessing both the data file and deferred update file to read a page. The SPDU method removes this overhead by using an in-memory data structure called the log table index. The log table index stores the offsets of the pages stored in the log file. Thus, we can find out whether a certain page is stored in the log file or in the data file by searching the log table index. The log table index in SPDU is similar to the page mapping table in the shadow-page method. \(^{[33]}\)

\(^{[33]}\) This has been patented in the U.S. \(^{[33]}\).
method in the sense that they refer to the most recent position where an updated page is stored. But, the difference is that all the updates in the log table index are reflected back to the data file when the transaction commits initializing the log table index while, in the shadow-page method, they are retained in the newly allocated pages pointed to by the updated page mapping table.

An entry of the log table index consists of \(<\text{pageid}, \text{offset}>\) pair. Here, \text{pageid} is the pageid of an original page in the data file, and \text{offset} is the offset for the page in the log file (i.e., a physical pageid in the log file). The entire set of pages of the database is stored in the data file. If we update a page in the data file, we append the updated page in the log file. We also store \(<\text{pageid}, \text{offset}>\) pair for the page into the log table index. Figure 5 shows page mapping in the SPDU method using the log table index.

In the data file, \text{pageid} of a page is equal to \text{offset} of the page since the DBMS maintains the pages in the order of \text{pageid}. However, in the log file, \text{pageid} of a page is different from \text{offset} of the page since we store updated pages according to the order updates occurred. In Figure 5, we update pages 3, 7, 1, and 9 in this order. When we need to access a page, we need to find out whether the page is stored in the data file or in the log file by searching the log table index. If it is stored in the log table index (e.g., pages 1, 3, 7 or 9 in Figure 5), we access the log file by using the \text{offset} stored in the log table index. Otherwise, we access the data file by using \text{pageid} of the page as the offset itself.

![Figure 5: Page mapping using the log table index in SPDU method.](image)

Figure 6 shows the algorithms for six basic operations of the SPDU method: (1) writing a page, (2) reading a page, (3) committing a transaction, (4) aborting a transaction, and (5) restarting the system, and (6) post commit processing for transaction commit and system restart.
Procedure Write_Page():
Inputs: (1) pageid /* page identifier of the page to be written */
(2) page_data /*content of the page having pageid */
Algorithm:
/* Step 1. Lookup the log table index */
offset := log_table_index.lookup (pageid);
/* Step 2. Write page_data to the log file */
IF (offset = NULL) THEN /* The page of pageid does not exist */
    Append page_data to the log file and return a new offset new_offset in the log file;
    log_table_index.add_entry (pageid, new_offset);
ELSE /* The page of pageid exists */
    Overwrite page_data to its original position offset in the log file;
END /* IF */
Procedure Read_Page():
Input: pageid /* page identifier of the page to be read */
Output: page_data /* content of the page of pageid */
Algorithm:
/* Step 1. Lookup the log table index */
offset := log_table_index.lookup (pageid);
/* Step 2. Read the page */
IF (offset = NULL) THEN /* The page exists in the data file */
    Return the page of pageid from the data file;
ELSE /* The page exists in the log file */
    Return the page stored at offset in the log file;
END /* IF */
Procedure Commit_Transaction():
Algorithm:
/* Step 1. Flush all dirty pages in the DBMS buffer to the disk */
FOR EACH dirty_page in the DBMS buffer DO
    Write_Page (dirty_page.pageid, dirty_page.content);
/* Step 2. Set commit_flag to TRUE */
Set commit_flag to TRUE and flush it to the disk; /* commit_flag is stored in the master page of the log file */
/* Step 3. Perform post commit processing */
Copy_AllPages_in_LogFile_to_DataFile ();
/* Step 4. Set commit_flag to FALSE */
Set commit_flag to FALSE and flush it to the disk;
/* Step 5. Initialize the log file and the log table index */
Initialize the log file and the log table index;
Procedure Abort_Transaction():
Algorithm:
/* Step 1. Invalidate all dirty pages in the DBMS buffer */
FOR EACH dirty_page in the DBMS buffer DO
    Invalidate dirty_page;
/* Step 2. Initialize the log file and the log table index */
Initialize the log file and the log table index;
Procedure Restart_System():
Algorithm:
/* Step 1. Redo committed transactions in the log file */
IF (commit_flag = TRUE) THEN
    Copy_AllPages_in_LogFile_to_DataFile ();
    Set commit_flag to FALSE and flush it to the disk;
END /* IF */
/* Step 2. Initialize the log file and the log table index */
Initialize the log file and the log table index;
Procedure Copy_AllPages_in_LogFile_to_DataFile(): /* post commit processing */
Algorithm:
/* Step 1. Overwrite each page in the log file to the data file */
FOR EACH page of pageid in the log file DO
    Overwrite page to the data file at the offset pageid;
Figure 6: Algorithms for the Shadow-Page Deferred-Update (SPDU) method.
Write\_Page takes pageid, the page identifier, and page\_data, the content of the page, as inputs. In Step 1, we look up the log table index to find whether the page to be written exists in the log file. In Step 2, if it exists in the log file, we overwrite it with the page\_data; if not, we allocate a new page in the log file, write page\_data into the new page, and add an entry <pageid, offset> to the log table index.

Read\_Page takes pageid as the input and returns page\_data, as the output. In Step 1, we look up the log table index to check whether the page to be read exists in the log file. In Step 2, if it exists in the log file, we read the page from the log file using offset; if not, we read the page from the data file.

Commit\_Transaction commits the transaction and copies the pages updated by the transaction from the log file to the data file. In Step 1, we flush every dirty page in the DBMS buffer to the log file and to the disk. In Step 2, we set the commit\_flag to TRUE in the master page\_9 of the log file and flush it to disk. The transaction commit is completed atomically during Step 2. In Step 3, we perform post commit processing by calling Copy\_AllPages\_in\_LogFile\_to\_DataFile procedure. The procedure reads each page in the log file, gets its pageid from the log table index, and copy its content into the original place in the data file using pageid. In Step 4, we set the commit\_flag to FALSE and flush it to disk to mark that post commit processing has been completed. In Step 5, we initialize the log file and the log table index.

Abort\_Transaction rolls back every write performed in the transaction. In Step 1, we invalidate every dirty page in the DBMS buffer by setting valid flag for the page to FALSE. In Step 2, we initialize the log file and the log table index.

Restart\_System initializes the system. In Step 1, if the system has crashed during the post commit processing (i.e., if commit\_flag is TRUE), we restart the post commit processing. In Step 2, we initialize the log file and the log table index to roll back the updates done in the uncommitted pages.

\footnote{This is the first page of the log file.}

\footnote{When crash occurs during post commit processing, consistency of the data file is violated. To recover consistency, post commit processing must be repeated from the beginning to the end. Thus, post commit processing is made idempotent to make repetitive crashes and restarts of post commit processing still guarantee consistency of the data file if completed to the end.}
4.2 Shadow-Page Deferred-Update Recovery Method for DFS (SPDU/DFS)

In this section, we present the shadow-page deferred-update recovery method for DFS (simply, SPDU/DFS) that modifies the SPDU method to use the DFS as the storage. The modifications for SPDU/DFS are as follows: (1) We manage the storage in the unit of the meta DFS file instead of the file. (2) We propose enhanced techniques to resolve inefficiencies of the SPDU algorithms incurred by the characteristics of the DFS.

By managing the data and log file by the Meta DFS File Manager, the SPDU/DFS method has the following strengths. (1) If the data file were composed of only one DFS file, a DFS file remake would occur for the entire data file whenever the system copies updated pages in the log file to the data file during a transaction commit. In the SPDU/DFS method, by managing a data file as a meta DFS file, the system performs DFS file remake only in the unit of the DFS block. (2) Likewise, if the log file were composed of one DFS file, a DFS file remake would occur for the entire log file whenever the system appends a page to the log file. By using a meta DFS file for the log file, however, we can have the same effect as with the data file.

The rest of the section describes further enhancements to solve inefficiencies that would arise when we directly apply the SPDU method to the DFS. Since the DFS block, a unit of I/O for a meta DFS file, is much larger than the DBMS page, inefficiency is incurred when we need to modify only a tiny part of the DFS block. In Section 4.2.1–4.2.3 we present three techniques for enhancement to alleviate this problem.

4.2.1 DFS block update buffer

To reflect the updated pages into the log meta DFS file in the unit of the DFS block, we introduce a DFS block update buffer whose size is identical to that of one DFS block. First, we accumulate the updated pages in the DFS block update buffer. This is possible since updated pages are written sequentially in the log file. Then, the system writes out the buffer when it is full or at transaction commit. This reduces the number of DFS file remakes.
Due to the DFS block update buffer, we should modify the page mapping of SPDU for SPDU/DFS. Figure 7 shows the modified page mapping. When we access a page, we should consider not only the data and log files but also the DFS block update buffer since recently updated pages reside in the buffer. Thus, when we access a page, we first check whether the page resides in the DFS block update buffer. If it does, we access it from the DFS block update buffer; otherwise, we choose the data meta DFS file or log meta DFS file using the log table index in the same way as in SPDU. In the log table index, we modify the offset in a log table entry to a pair $<\text{block}_\text{id}, \text{b_offset}>$ where $\text{b_offset}$ is an offset within the DFS block having $\text{block}_\text{id}$.

![Log table index]

| page\text{id} | offset |
|---------------|--------|
| 3             | $<0,0>$|
| 7             | $<0,1>$|
| ...           | ...    |
| 1             | $<k,0>$|
| 9             | $<k+1,0>$|

$x$ : a page whose page\text{id} is $x$

![Data Meta DFS File]

![Log Meta DFS File]

![DFS Block Update Buffer]

Figure 7: Page mapping in SPDU/DFS.

4.2.2 Post Commit Processing in the Unit of the DFS block

In SPDU, during Commit\text{\_Transaction} and Restart\text{\_System}, we copy updated pages in the log file to the data file (i.e., post commit processing). This post commit processing process would become extremely inefficient for SPDU/DFS since a DFS file remake occurs every time a page is copied. This inefficiency stems from the fact that updates pages for a DFS block in the data meta DFS file are stored scattered in the log meta DFS file. To resolve this problem, we sort the pages in the log meta DFS file to be able to copy the updated pages to the data meta DFS file in the unit of the DFS block. Specifically, (1) we
sort all the updated pages in the log meta DFS file according to pageid and group them in the unit of the DFS block. (2) We load each DFS block containing the updated pages from the data meta DFS file to the main memory, update the DFS block with the updated pages in the log meta DFS file, and write it back to the data meta DFS file through a DFS file remake. This incurs only one DFS file remake for one DFS block instead of for one page. In addition, when there have been multiple updates in the same page, this method allows us to reflect it only once by using the last update to the page.

4.2.3 Deferred Post Commit Processing

In Section 4.2.2, we improved the efficiency of post commit processing. But, post commit processing is inherently inefficient since the DFS file remake is an expensive operation itself. To alleviate this problem, we defer post commit processing until multiple transactions commit rather than doing it after each commit. Specifically, we perform post commit processing in a batch (1) periodically or (2) when the size of the log meta DFS file exceeds a pre-determined value.

Due to deferred post commit processing, the log meta DFS file normally contains not only uncommitted data but also committed data. Thus, two new issues arise. First, we need to distinguish committed data from uncommitted data in the log meta DFS file to correctly process transaction abort or system restart. For this, we introduce a new flag in each DFS block in the log meta DFS file called commit_complete. If commit_complete is TRUE, the data in the DFS block must have been committed; if not, the data have not been committed. The commit_complete flag plays the role of a checkpoint allowing us to know that the data in the DFS block with commit_complete set TRUE and in all the prior DFS blocks have been committed since we only deal with serial schedules of write operations. Therefore, when the transaction is aborted or the system is restarted, we delete DFS blocks in the log meta DFS file from the most recent DFS block in the reverse order until we meet a DFS block with the commit_complete flag set TRUE.

11In the worst case, each page of a DFS block in the log meta DFS file can be stored in a different DFS block in the data meta DFS file. This indicates that \( \frac{64MB}{4KB} = 16,000 \) DFS file remakes could occur to copy one DFS block in the log meta DFS file back to the data meta DFS file, if the size of a DFS block is 64MB and that of a page is 4KB.
Second, when multiple transactions are working simultaneously, a transaction may need to access updated data committed by another transaction. To access the most recent data, each DBMS process should keep the log table index up to date reflecting the most recent state of the database. For this, we reconstruct the log table index for a DBMS process by reading the log meta DFS file at the time when the process acquires a read or write lock. Since we use the database lock, the database cannot be updated by other DBMS processes after acquiring the lock. Therefore, it guarantees that each DBMS process can access the most recent state of the database. Figure 8 shows an example of reconstructing the log table index when two DBMS processes (P1 and P2) are running simultaneously. Initially, there is no updated pages in the database, and then, P1 acquires a lock, updates pages 5 and 3, and releases a lock. Thus, these updates are reflected to the log meta DFS file and the log table index for P1. When P2 acquires the lock, we reconstruct the log table index for P2 to reflect the most recent state of the database, i.e., to include pages updated by P1.

![Figure 8: Reconstruction of the log table index.](Image)

12For efficient reconstructing of the log table index, we store a list of pages contained in each DFS block at the end of the DFS block. We can reconstruct the log table index by accessing only the list of each DFS block without having to read the entire set of pages in the DFS block.
5 Concurrency Control

In this section, we present the concurrency control method of Odysseus/DFS. Odysseus/DFS uses a locking-based concurrency control method. We present the way we implement read/write lock operations for concurrency control.

An important property of a lock is its granularity. As discussed in Section 4, we use the database lock for concurrency control to achieve serial schedules for write transactions. We implement read/write locks using Zookeeper [36] as follows. A DBMS process that wants to acquire a lock connects to Zookeeper, requests the lock, and wait until acquiring the lock. When the process satisfies conditions to acquire the lock, it finishes waiting and acquires the lock. We also implement a lock compatibility matrix realizing write/write and read/write conflicts using Zookeeper as follows. A process that requested a read lock acquires it after all the write locks requested prior to the read lock have been released. A process that requested a write lock acquires it after all the (read or write) locks requested prior to the write lock have been released.

A detailed implementation is as follows. Zookeeper manages a data structure similar to an O/S directory/file. We implement locks by using the API functions for managing Zookeeper files since Zookeeper itself does not support API functions controlling locks directly. We create a Zookeeper directory for a data meta DFS file and create a Zookeeper file in the directory for a particular DBMS lock request. Specifically, when a DBMS process wants to acquire a lock for a data meta DFS file, it creates a Zookeeper file with the file name of the form \((\text{lock type}, \text{lockid})\) in the Zookeeper directory representing the data meta DFS file. Here, \(\text{lock type}\) is either a read lock or a write lock; \(\text{lockid}\) is incrementally assigned by Zookeeper in the order of the time of lock request. When a lock creation fails or a lock is released, the corresponding Zookeeper file is destroyed.

Locks are granted in the order of lockids, i.e., in the order the lock requests arrive at Zookeeper. Specifically, when a DBMS process requests a read lock, if there are only read locks or there are write locks that have a larger lockid than that of the current lock request, it instantly acquires the read lock. However, if there are write locks that have lockid’s smaller than that of the read lock requested, it sets
a watcher to the write lock that has been requested last and waits. When the lock observed by the
watcher is released, the current process is awakened and acquires the read lock.

When a DBMS process requests a write lock, it instantly acquires the write lock only when all the
lockids of the existing locks, except a read lock that is possibility owned already by the DBMS process
itself, are bigger than the lockid of the write lock requested. However, if there is any lock that has a
lockid smaller than the write lock requested, the current process waits after setting a watcher to the
lock that has been requested last. When a lock observed by the watcher is released, the current process
is awakened and acquires the write lock.

6 Performance Evaluation

6.1 Experiment Setting

In this section, we compare the performance of Odysseus/DFS with that of Hbase, a representative
NoSQL system, to show the effect of using the DBMS functionality. In particular, we show the effect of
using the index since it affects the performance of the system. The other DBMS functionalities make
Odysseus/DFS more usable than Hbase but does not much affect the performance. We also compare the
performance of Odysseus/DFS with that of an RDBMS using local storage to show that the performance
overhead of Odysseus/DFS is not significant despite supporting scalability and reliability through the
DFS, which are not supported by the RDBMS. We conduct experiments on read and write operations
for sequential and random workloads: (1) sequential read, (2) sequential write, (3) random read, and (4)
random write.

In order to set up Odysseus/DFS and Hbase, we use a cluster of nine nodes: one master and eight
slaves. Each node consists of 3.2GHz Intel Quad-Core CPU, 8GB RAM and one 1TB hard disk. Nodes
are connected by a 1Gbps network switch. The average transfer rate of the hard disk is 120MByte/s.
The average network transfer rate is 80MByte/s.
To implement Odysseus/DFS, we use the Odysseus DBMS [32, 35] (coarse-granule locking version), replacing the file system its own and transaction manager with the Meta DFS File Manager and the DFS Transaction Manager. We also use the Odysseus DBMS when we conduct experiments for the RDBMS using the local storage for a fair comparison. We use the entire database as the locking granule of the Odysseus/DFS and the RDBMS (Odysseus) to employ a large locking granule realizing serial schedules for write transactions. As the storage for Odysseus/DFS and Hbase, we use HDFS (binary version 1.0.3) from http://hadoop.apache.org. We use Hbase binary version 0.94.7 with default settings for configuration. Odysseus DBMS has been implemented in 450,000 lines of precision C and C++ codes [32, 34, 35]. Meta DFS File Manager of Odysseus/DFS is implemented in C on top of the C language API of DFS Client. HDFS and Hbase are written in Java.

In the experiments, we use the synthetic data set generated by Pavlo et al. [25]14. This data set models rankings and visit logs of web pages. It has three tables: Web Document, Ranking, and UserVisits. For our experiments, we use the UserVisits table, which has the largest number of tuples among the three tables. There are 155 million tuples in the UserVisits table. The schema of the database is described in Figure 9. For the experiments, we choose the visitDate attribute to cluster the UserVisits table. Since Hbase does not support SQL, we hand-coded the schema equivalent to the one defined in SQL. Specifically, we map an attribute of SQL to a column of Hbase.

Figure 10 shows the queries used for the experiments. Odysseus/DFS and the RDBMS using local storage process the queries through SQL, and Hbase through a hand-coded Java program equivalent to SQL. The Scan query reads 100,000 tuples of the table sequentially. The Insert query inserts 10,000 new tuples to the table sequentially. To make the sequential write workload for the Insert query, we inserted the data to be ordered by the clustering attribute. The Select query retrieves tuples satisfying the condition where the sourceIP attribute is 160.110.44.44 in the table. This query reads data randomly when the non-clustering attribute sourceIP has a secondary index. Otherwise, it scans the

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13Odysseus supports not only large locking granularity, i.e., database-level locking, but also small locking granularity, i.e., record-level locking.

14This data set was also used by several other studies [2, 12, 13] on big data management.

15The number of tuples that satisfy the condition is 70; thus, the selectivity is $4.5 \times 10^{-7}$. 
(SQL)
CREATE TABLE UserVisits ( sourceIP VARCHAR(16), destURL VARCHAR(100), visitDate DATE,
adRevenue FLOAT, userAgent VARCHAR(64), countryCode VARCHAR(3),
languageCode VARCHAR(6), searchWord VARCHAR(32), duration INT );
CREATE INDEX uservisits_sourceip_idx ON UserVisits ( sourceIP );

(HBase)
HBaseAdmin hbase = new HBaseAdmin(config);
HTableDescriptor tdesc = new HTableDescriptor(tableName);
String[] colName = new String[] {'sourceIP', 'destURL', 'visitDate', 'adRevenue',
    'userAgent', 'countryCode', 'languageCode', 'searchWord', 'duration'};
for(int i=0; i<colName.length; i++) {
    HColumnDescriptor cdesc = new HColumnDescriptor(colName[i].getBytes());
    tdesc.addFamily(cdesc);
}
hbase.createTable(tdesc);

Figure 9: The schema of the database used in the experiments.

The entire table sequentially. The Update query finds the tuples satisfying the condition where the sourceIP attribute is 160.110.44.44 and updates the countryCode attribute to ‘ABC’. As the Select query, it reads data randomly only if the sourceIP has a secondary index.

Scan: SELECT * FROM UserVisits LIMIT 100000;
Insert: INSERT INTO UserVisits VALUES ( ... ); (repeat 10000 times)
Select: SELECT * FROM UserVisits WHERE sourceIP = '160.110.44.44';
Update: UPDATE FROM UserVisits SET countryCode = 'ABC' WHERE sourceIP = '160.110.44.44';

Figure 10: The SQL queries used in the experiments.

The elapsed time of the SQL queries is measured. All the experiments are performed in cold start; in order to obtain consistent results, we flush the DBMS buffers, O/S file buffers, and disk buffers before executing each query. We average the elapsed times of five identical executions of each query.


6.2 Performance Results

6.2.1 Comparison with NoSQL

In this section, we compare performance of Odysseus/DFS and Hbase. While Hbase cannot support a secondary index, Odysseus/DFS does. Thus, Odysseus/DFS outperforms Hbase for the queries that include predicates for the non-clustering attribute having a secondary index. Among the queries in Figure 10 Scan and Update are such queries.

Figure 11 shows the performance of Odysseus/DFS and Hbase for Scan and Update queries. Odysseus/DFS (w/w index) represents the performance of Odysseus/DFS using a secondary index on the sourceIP attribute. Odysseus/DFS (w/o index) represents the performance without using an index. The result shows that Odysseus/DFS (w/o index) is faster than Hbase by 2.2 times, and Odysseus/DFS (w/w index) is faster than Hbase by 18.6~27.2 times. First, let us focus on the former result. It is difficult to directly compare Odysseus/DFS with Hbase since the former uses a DBMS while the latter a key-value store. However, we conjecture that the primary reasons for the performance difference are from the storage structures and the programming languages. Specifically, Hbase stores the data in column-store. Thus, processing queries involving multiple attributes is inefficient. Moreover, Hbase is implemented in Java while Odysseus/DFS in C. In this paper, we focus on the performance difference by the DBMS functionality, i.e., secondary indexes, rather than the system-oriented differences. Second, let us focus on the latter result. Here, if we remove the system-oriented performance difference (i.e., 2.2 times), we observe that the actual performance enhancement due to using indexes in Odysseus/DFS compared with Hbase is 8.6~12 times.

6.2.2 Comparison with an RDBMS using local storage

In this section, we show performance overhead incurred when the DBMS uses the DFS in place of local disk as the storage. We conduct experiments for four workloads discussed above. Figure 12 shows the result of sequential read and sequential write obtained by running Scan and Insert queries. In sequential read, Odysseus/DFS has 31% additional overhead compared to Odysseus with local storage.
This overhead is due to the network bottleneck overhead described in Section 3.2, i.e., it is incurred when the network speed cannot catch up with the transfer rate of magnetic disks. In sequential write, the performance of Odysseus/DFS is 19% faster than that of Odysseus with local storage since the former uses deferred post commit processing. Since post commit processing can be done in the background when the workload is not heavy, its overhead can be saved.

Figure 11: Results of Scan and Update queries of Odysseus/DFS and Hbase.

Figure 12: Results of sequential read and write operations of Odysseus/DFS and Odysseus.

Figure 13 shows the results of random read and random write obtained by running Select and Update queries. In random read, Odysseus/DFS has 67% additional overhead compared to Odysseus. This overhead is due to the network transfer overhead described in Section 3.2, i.e., it is incurred by network transfer time for the data pages randomly accessed through the DFS. In random write, Odysseus/DFS has 54% additional overhead compared to Odysseus due to a similar reason. To process
the random write query, the system first searches for the tuples that satisfy the condition and then 
update them. Most of the query processing time is for searching since only 70 tuples out of 155 million 
tuples read are updated, rendering the updating time negligible. Therefore, the result of random write 
has a similar tendency to that of random read.

![Graph](image)

Figure 13: Results of random read and write operations of Odysseus/DFS and Odysseus.

We observe the following from the experiments:

- The performance of Odysseus/DFS is comparable to that of Odysseus even though the former 
supports scalability by using the DFS as the storage. It is shown to be 0.73 ~ 1.67 times that of 
Odysseus. Odysseus/DFS has performance improvement over Odysseus in sequential write since 
it defers post commit processing as discussed in Section 1.2.3. It has performance degradation 
compared to Odysseus in sequential read since the network bandwidth does not catch up with the 
disk transfer rate, and in random read and random write, due to network transfer time. These 
are unavoidable in a distributed environment.

7 Conclusions

The contributions of the paper are as follows. First, we have proposed a new architecture integrating 
an RDBMS with the DFS for transaction processing of big data. By using the DFS as the storage of 
an RDBMS, we can extend the scalability and reliability of the RDBMS. Second, we have proposed the 
notion of the meta DFS file to be used as the storage for an RDBMS allowing in-place overwriting and
appending operations to the DFS by the unit of the DFS block. Third, we have presented techniques for
transaction management that support update, recovery, and concurrency control while considering the
characteristics of the DFS. The transaction method we implemented in this paper supports only serial
schedules with respect to write transactions and concurrent schedules with respect to read transactions
employing coarse-granularity locking in order to reduce the locking overhead. Fourth, we have presented
experimental results to compare the performance of the RDBMS using the DFS as the storage with those
of NoSQL-based key-value store and the RDBMS using local disk as the storage. The result shows
that Odysseus/DFS has an advantage over Hbase (18.6~27.2 times) due to availability of secondary
indexes and over relational DBMS in sequential write due to deferred post commit processing; it has a
disadvantage over a relational DBMS in sequential read (31%) due to the network bottleneck overhead
and random read/write (54%~67%) due to the network transfer overhead.

The strengths of Odysseus/DFS are as follows. First, it has DBMS-level functionality compared
to NoSQL systems. That is, Odysseus/DFS offers more convenience and generality for developing and
maintaining applications. Since the DFS and key-value store have low-level APIs, it is difficult to use
them for developing applications while it is much easier and less error prone to use Odysseus/DFS
directly utilizing high-level DBMS functionality.

Second, Odysseus/DFS provides more scalability and fault-tolerance for the storage compared to
the conventional RDBMS. Expanding the storage using a single-node RDBMS with a disk array or SAN
or a distributed/parallel DBMS has limitations in scalability, availability, and economical feasibility. On
the other hand, Odysseus/DFS overcomes these limitations by using the DFS directly as the storage.

Third, we have shown through experiments that the performance of Odysseus/DFS is superior
to Hbase even though Odysseus/DFS provides high-level DBMS functionality. Our experiments also
show that performance degradation of Odysseus/DFS compared to an RDBMS with local storage is not
significant even though Odysseus/DFS provides much better scalability for the storage.

For effective management of large-scale big data, supporting both scalability of the storage and
DBMS-level functionality is important. Odysseus/DFS is the first work to support a general purpose
RDBMS for NoSQL systems. We have shown that Odysseus/DFS is an efficient system for processing transactions in big data.

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