UStore: A Distributed Storage With Rich Semantics

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Abstract

Today’s storage systems expose abstractions which are either too low-level (e.g., key-value store, raw-block store) that they require developers to re-invent the wheels, or too high-level (e.g., relational databases, Git) that they lack generality to support many classes of applications. In this work, we propose and implement a general distributed data storage system, called UStore, which has rich semantics. UStore delivers three key properties, namely immutability, sharing and security, which unify and add values to many classes of today’s applications, and which also open the door for new applications. By keeping the core properties within the storage, UStore helps reduce application development efforts while offering high performance at hand. The storage embraces current hardware trends as key enablers. It is built around a data-structure similar to that of Git, a popular source code versioning system, but it also synthesizes many designs from distributed systems and databases. Our current implementation of UStore has better performance than general in-memory key-value storage systems, especially for version scan operations. We port and evaluate four applications on top of UStore: a Git-like application, a collaborative data science application, a transaction management application, and a blockchain application. We demonstrate that UStore enables faster development and the UStore-backed applications can have better performance than the existing implementations.

Keywords: Versioning, Branching, Collaborative Analytics, Blockchain

1 Introduction

Application developers today can choose from a vast array of distributed storage systems. As storage costs are going down drastically, storage systems differentiate themselves by the levels of abstractions offered to the applications. At one extreme, key-value stores such as Dynamo\textsuperscript{25}, Voldemort\textsuperscript{7}, Redis\textsuperscript{8}, Hyperdex\textsuperscript{28} provide simple interface to build highly available and scalable applications. However, many systems have more complex data models than simple key-value records, for instance social graphs or images, such that to implement them on top of a key-value storage requires re-building complex software stacks and therefore risks re-inventing the wheel. At the other extreme, relational databases are highly optimized, but enforce strict relational data models which limit the range of applications, and the ACID guarantees limit their scalability. Currently, we see a shift towards more structured storage systems, for examples, TAO\textsuperscript{16}, MongoDB\textsuperscript{6}, PNUTS\textsuperscript{20}, LogBase\textsuperscript{68}, which offer more scalability, but their data models are specific to the given domain, therefore they do not generalize well to other domains. Amid these choices, we ask the question whether there is still a gap to be filled by another storage system, and if there is, what would be the right level of abstraction?

We observe that many recent distributed applications share three core properties. First, data immutability, in which data never changes and any update results in a new version, is being exploited to build popular version control systems like Git\textsuperscript{8}. Immutability also plays a key role in many data intensive systems\textsuperscript{33} wherein it helps simplify the design for fault tolerance and replication. MapReduce\textsuperscript{23} and Dyrad\textsuperscript{36}, for instance, split computation tasks into smaller units each taking immutable input and storing immutable output to HDFS or GFS. Immutability in these settings make it easy to handle failures by simply restarting the units without complex coordination. Second, data sharing is the key property in the growing number of social network and collaborative applications, driven by the growth of user-generated data and the need for collaborative analytics\textsuperscript{52}. Early peer-to-peer content sharing systems\textsuperscript{39,19} are being replaced by more centralized alternatives\textsuperscript{15} with dif-
different data models and collaborative workflows. For example, DataHub [15] exposes a dataset model with infrequent updates, whereas GoogleDocs assumes text documents and real-time updates. Third, data security is becoming increasingly important due to data breaches arising from insider threats (NSA, Target, Sony hack, for example), and due to the vulnerability of third-party cloud providers to attacks. For confidentiality protection, systems such as CryptDb [50] and M2R [26] enable database and big-data analytics tasks to be performed over encrypted data, by employing novel encryption schemes and trusted hardwares. Blockchain systems like Bitcoin [50], Ethereum [30] and Hyperledger [35] ensure integrity of the data stored on a shared ledger even under Byzantine failures.

Given these trends, we argue that there are clear benefits in unifying data immutability, sharing and security in a single storage system. By focusing on optimizing these properties in the storage, one immediate value is to reduce development efforts for new applications that need any combination of these properties, as they are provided out of the box. In addition, existing applications can be ported to the new storage, thereby achieving all three properties at the same time and with better performance.

In this paper, we propose a new distributed storage system, called UStore, that accomplishes the following goals. First, it has rich semantics: the storage supports data immutability, sharing and security. Second, it is flexible: performance trade-offs can be tuned, and it can be easily extended to accommodate new hardware or application’s needs. Third, it is efficient and scalable: it offers high throughput and low latency, and it can scale out to many servers. Existing systems fall short at accomplishing all three goals at the same time. For instance, temporal databases [40] or HDFS provide only immutability, whereas P2P systems [19] focus mainly on sharing. Git [3] and Datahub [15] implement both immutability and sharing, but forgo security. Furthermore, Git is designed for P2P environment, thus it is limited in efficiency [9]. Datahub is restricted to relational data models (hence, it is inflexible) and has not been shown to scale to multiple servers. Several systems like SPORC [29] and Bitcoin [50] support all three properties, but they are not general and efficient enough for other applications beside collaborative text editing and crypto-currency.

UStore’s data model is based on a novel data structure called UObject, which is identified by a unique key and its content is a direct acyclic graph of UNode objects. Each UNode in the graph is identified by a unique version, its value contains the data, and connections between them represent derivation relation between different versions of the data. An update to UObject creates a new version in the graph, and the complete version history can be traced by following the backward pointers. This is similar to the commit history in Git, but unlike Git, US-

tore partitions and replicates UNode objects over multiple nodes for better read and write performance. UStore’s partitioning scheme is locality-aware, in the sense that related versions are likely to be grouped together in the same node. Together with caching, and native support for Remote Direct Memory Access (RMDA), UStore can deliver high performance on operations that scan historical versions. UStore supports non-realtime collaborative workflows by providing a publish/subscribe channel with which users can be notified when there are new versions of the objects of interest. It guarantees integrity of both the data and version history against untrusted providers by using tamper-evident version numbers which are similar to hash pointers in blockchains. Furthermore, it allows for flexible and fine-grained sharing policies based on the entire UObject or a set of UNode objects. UStore provides a number of parameters for tuning performance trade-offs between the access operations, storage capacity and overall availability guarantees. Finally, UStore supports push-down semantics by allowing user-defined logics for data compression, and for detecting and merging of data conflicts.

We implement four applications on top of the current in-memory implementation of UStore. The first application is an extension of Git for distributed settings, in which multiple users collaborate on a single repository. Another application implements the relational data model and data science workflows as supported in Datahub [15]. The third application is a transaction management protocol based on TARDIS [21] that supports weak consistency with branch-and-merge semantics. Finally, we implement a simple private blockchain application based on Ethereum [30] which supports analytical queries on the blockchain data. Each application is implemented in fewer than 1300 lines of code, demonstrating that UStore enables fast application development. We then benchmark UStore’s performance individually, and evaluate the four applications against systems that support the same operations. The results show that UStore’s performance is comparable to Redis in basic read/write operations, and is better than Redis in scanning operations. The Git-like application achieves up to 3 orders of magnitude lower latency than Git in versioning operations (commit and checkout). The collaborative data science application achieves up to 10x lower latency than Decibel [45] in 3 out of 4 popular queries. The transaction management application reduces the number of states accessed by 2 orders of magnitudes compared to TARDIS. The blockchain application outperforms Ethereum by 2 orders of magnitudes in 4 out of 5 queries.
In summary, in this paper we make the following contributions:

- We identify common trends in today’s distributed applications and argue for the need of a distributed storage targeting a large classes of existing and emerging applications.
- We design and implement UStore, a flexible, efficient and scalable distributed storage with three core properties: data immutability, sharing and security.
- We benchmark UStore against Redis, showing comparable performance for basic operations and significant improvement for scan operations. We implement four applications on top of UStore, namely Git, collaborative data science, transaction management and blockchain. We evaluate them against systems supporting the same operations, and demonstrate that UStore improve the applications’ performance while reducing development efforts.

In the next section, we motivate UStore by discussing the trends in distributed applications and the challenges faced by these systems. We present the detailed design in Section 3 and describe our implementation of four applications in Section 4. We report the performance of UStore and of its applications in Section 5. We discuss UStore’s current states and future work in Section 6, before concluding in Section 7.

### Table 1: Systems built around data immutability, sharing and security.

| System      | Immutability | Sharing | Security |
|-------------|--------------|---------|----------|
| GFS/HDFS    | ✓            |         |          |
| RDD         | ✓            |         |          |
| Datomic     | ✓            |         |          |
| LogBase     | ✓            |         |          |
| Bittorent   |              | ✓       |          |
| Dropbox     |              | ✓       |          |
| Tahoe LAFS  | ✓            | ✓       |          |
| Datahub     | ✓            | ✓       |          |
| Git         | ✓            | ✓       |          |
| Irmin       | ✓            | ✓       |          |
| Noms        | ✓            | ✓       |          |
| Pachyderm   | ✓            | ✓       |          |
| Ori         |              | ✓       |          |
| SUNDR       | ✓            | ✓       | ✓        |
| Bitcoin     | ✓            | ✓       | ✓        |
| Ethereum    | ✓            | ✓       | ✓        |
| UStore      | ✓            | ✓       | ✓        |

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### Related Work and Motivations

In this section, we discuss several trends in distributed systems that underpin many interesting applications, including version control, data versioning, collaboration and security-aware applications, and related work. Table 1 lists research and open source systems along three common properties: immutability, sharing and security. We then review new hardware capabilities that are key enablers for next-generation distributed systems.

#### 2.1 Immutability

Git [3] is a widely used open-source distributed version control system (DVCS), which outperforms other VCS (such as Subversion, CVS, Perforce) due to its unique features like cheap local branching, convenient staging areas, and multiple workflows. Fundamental to Git’s design is data immutability, that is, all changes committed to Git are permanently archived in version histories. Viewed as an append-only key-value store, Git allows efficient tracking of the entire version history. Furthermore, it is easy in Git to compare, merge and resolve conflicts over branches. Git can automatically resolve many conflicts arising from source code versioning, and only notifies users for conflicts it cannot resolve. Git enables offline collaboration models in decentralized, P2P settings in which each user has a complete copy of the repository.

Beside Git, we observe immutability in many other data-oriented applications. In particular, massively parallel systems such as MapReduce and Dryad are based on immutable inputs stored in HDFS or GFS, which greatly simplifies failure handling by restarting the failed tasks. Similarly, Spark [69] is based on Resilient Distributed Datasets (RDDs) abstraction, which are indeed immutable datasets tracking the operation history. Other examples of immutability include LSM-like data storages such as HBase [1], in which immutability enables superior write throughput for ingesting updates while simplifying failure recovery.

One particular manifestation of immutability in data management systems is data versioning, which has been employed for tolerating failures, errors and intrusions, and for analysis of data modification history. ElephantFS [62] is one of the first file systems with built-in multi-version support. Later systems like S4 [66], CVFS [64], RepareStore [71] and OceanStore [39], improve the early design by maintaining all versions in full scope and upon each update operation. Most of these systems use journal/log-structure file system (e.g., SpriteLFS [58]) as the underlying storage, because they leverage the latter’s high performance in append-only workloads. In databases, data versioning techniques are used for transactional data access. Postgres [65], for example, achieved performance comparable to other database systems without versioning sup-
port. Fastrek \cite{18} enhanced Postgres with intrusion tolerance by maintaining an inter-transaction dependency graph based on the versioned data, and relying on the graph to resolve data access conflicts.

2.2 Sharing and Collaboration

The exponential growth of data can be attributed to the growth in user-generated, machine-generated data and the need to log and collect data for future analytics. Before the data can be meaningfully used, the owners must be able to share their data among each other and among different systems. Past \cite{59} and BitTorrent \cite{19}, for examples, are optimized for object discovery, durability, availability and network bandwidth. Data sharing among users is fundamental to recent social network platforms, for which many techniques have been developed to optimize both throughput and latency \cite{14}.

Efficient data sharing makes it possible to implement various collaboration models. Unlike classic multi-user, time-sharing systems like databases which give a user the illusion of owning the entire system, collaborative systems explicitly provide different views to different users, and synchronization between different views are directly observed and controlled by the users. Most collaborative systems expose file system interface where a set of files can be mounted locally from a remote server. Dropbox, NFS and CIFS, for example, assume centralized servers, whereas Git \cite{3}, IPFS \cite{4}, Ori \cite{47} work in decentralized settings. These systems employ lightweight synchronization techniques such as versioning and content-addressable files in order to minimize synchronization cost. They can be characterized by their supported workflows: from infrequent updates (version control systems like Git), frequent updates (shared file systems like Dropbox), to real-time updates (document editing systems like GoogleDocs). Recent systems such as DataHub \cite{15} expose a dataset interface to support collaborative big-data workloads. Datahub targets scientific domains wherein multiple users and teams perform data-intensive computations on shared data \cite{52}, for which existing databases or version control systems are inadequate.

2.3 Security

There is an inherent threat from moving data into the hand of untrusted parties, i.e. cloud providers. Recent high-profile data breaches and system attacks (NSA, Target, Sony hack, for example) further demonstrate the challenges in protecting data from insider threats. Protecting data confidentiality can be readily implemented on existing cloud storage systems, by simply encrypting the data. However, there is a need to perform computation on the encrypted data, for which systems like CryptDb \cite{56} employ homomorphic encryption schemes. In order to support a rich set of database operations, these systems make strong assumptions on the data and security model, which may not hold in practice \cite{51}.

Recent systems, namely Haven \cite{13} and M2R \cite{20}, rely on trusted hardware to deliver high security guarantee for general computations using small trusted code base.

In a collaborative setting with an untrusted provider, integrity protection refers to the ability to detect forks. Specifically, the provider can present different sequences of updates to the shared state to different users, thereby forking multiple views. SUNDRA \cite{43} is the first system to provide fork-consistent file systems, meaning that if the server presents two users with different views, these users can either never see each other’s view, or they can detect that there is a fork. Later works, such as Venus \cite{63} and Depot \cite{46} extended SUNDRA to improve performance and conflict resolutions. In the decentralized setting where peers distrust each other, recent blockchain systems achieve integrity for a global data structure resembling a ledger \cite{50,50,55}. In these systems, users reach agreement via distributed consensus protocols which can tolerate certain numbers of malicious adversaries. In public blockchain systems, in which peers can freely join and leave, the consensus protocol is based on proof-of-work which gives each user a probability of updating the blockchain proportional to his computing power. Recent proposals of private blockchains can achieve better performance by using cheaper consensus protocols such as PBFT \cite{17}.

2.4 Hardware Trend

The increased availability of large memory has given rise to in-memory computing \cite{67,70}, from general computing frameworks like Spark \cite{69}, to databases like Hyper \cite{38} and SAP HANA \cite{40}, or data storage systems like RAMCloud \cite{60} and Redis \cite{61}. In-memory systems deliver low latency and thus can be used for real-time analytics.

Beside memory, new hardware primitives such as Non-uniform Memory Access (NUMA) \cite{44}, Hardware Transactional Memory (HTM) \cite{42}, Remote Direct Memory Access (RDMA) networking \cite{37}, Non-Volatile memory (NVM) \cite{24}, etc. offer new opportunities to improve system performance by leveraging the hardware. However, changes in hardware often require re-examining the existing designs in order to fully exploit the hardware benefits. For example, Hyper \cite{41} proposes a new query evaluation framework to overcome overheads with non-NUMA-aware data access. PiLaF \cite{48}, HERD \cite{37}, and FaRM \cite{27} propose enhancement to existing key-value storage and transac-
3 UStore Design

In this section, we present the detailed design of UStore. The system follows a layered design, with the narrow waist being the core abstraction called UObject. We first discuss the high-level design goals, and then describe how we achieve them at different layers of the system.

3.1 Overview

Inspired by the software and hardware trends discussed in the previous section, we design UStore with three high-level goals.

**G1: Rich semantics.** UStore provides data immutability, data sharing, and data security out of the box. Once data is inserted, it remains unchanged. The data can be shared among applications and users in fine-grained manner. Finally, integrity of the data and of the update history are protected against untrusted cloud providers.

**G2: Flexibility.** UStore APIs give its applications freedom to configure and combine the immutability, sharing and security properties. It also allows user to push down application semantics via a number of well-defined interfaces.

**G3: Efficiency & scalability.** UStore delivers high throughput, low latency for its data access operations, and it can scale out to many nodes.

Figure 1 shows multiple layers of UStore’s stack. At the bottom, the physical layer is responsible for storing, distributing and replicating data over many servers. We consider settings in which servers belong to a number of independent administrative domains, i.e. they are mutually distrustful. The next layer contains UStore’s core data structure which bears some similarity to Git’s. In particular, it implements immutability with support for branching and merging. UStore differentiates from Git in the structure and operational semantics of each data value. The distinction to Git becomes more apparent at the next two layers. The APIs layer exposes access operations which are specific to a version of data. The view layer adds fine-grained access control, security, customizable consistency model and a notification service. Finally, applications such as transaction management, blockchains, data science collaboration, etc. can exploit UStore’s rich semantics by building directly on the APIs and the views from the lower layers.

The Git-like data structure embedded at the second layer makes up the narrow waist of the design. In other words, UStore enforces a single representation and unchanged semantics of this data structure, but allows for different implementations of the physical, view and application layers. By fixing the representation, UStore can accommodate innovations at the physical layer and changes in application requirements. This layered design achieves the three goals as follows. First, G1 is realized by the data representation and view layer. Second, flexibility (G2) is achieved by exposing parameters and application hooks at the physical layers for specifying constraints on resources, on distribution and replication strategies. In addition, UStore lets the applications overwrite the consistency view to implement their own models. Third, UStore’s high performance (G3) comes from the careful use of the available hardware at the physical layer.

3.2 Abstraction and APIs

UStore is based on a novel abstraction, called UObject, for reading and writing data. Each UObject manages all data related to a specific key and supports retrieval of existing values and tracking of version history.

3.2.1 UObject

A UObject is identified by a unique key, and comprises a directed acyclic graph (DAG), as shown in Figure 2. Each node in this graph, called UNode, contains a pair of data: a unique version number and the corresponding value of that key, as shown in Figure 3. The connections between Unodes represents derivation relations among different versions of the data. In other words, a UObject contains all historical information of a key. Its concrete data structure is as follows:
struct UObject {
    string key
    collection<UNode> versions
}

struct UNode {
    version_t version;
    string value;
    version_t prev_1, prev_2;
}

struct version_t {
    string h;
    int l;
    string n;
}

We have no restrictions on how each version can be extended. That is, a version can be extended multiple times, leading to independent branches, for example $v_2$ is extended to $v_5,v_7$ in Figure 2. Correspondingly, divergent branches can be combined (or merged), for example $v_2$ and $v_4$ are merged into $v_5$. This abstraction can be viewed as an extension of key-value, in which the application can treat each update as a $(key, version, value)$ tuple, and retrieve existing values via composite keys.

### 3.2.2 Versions

In UStore, version numbers not only serve as unique identifier of UNode objects, they also play a key role in security and load balancing. More specifically, UStore ensures three properties of version numbers:

1. **Unique**: UNode objects have distinct version numbers.
2. **Verifiable**: Version numbers can be used to prove integrity of the retrieved objects.
3. **Locality-aware load balancing**: UNode objects can be partitioned over multiple nodes, and objects of the same branch have high probabilities to be stored in the same node.

Essentially, a UStore version is a 3-field tuple:

$$v = (v.h, v.l, v.n)$$

where $v.h$ is the cryptographic hash tied to the object content, $v.l$ is the depth (from root of the DAG), and $v.n$ is a random value generated by a storage server. The root version is defined as $v_{NULL} = (NULL, NULL, NULL)$. We explain how UStore achieves its three properties later in this section.

### 3.2.3 APIs

To write a new value to a key, the application needs to specify the base version from which the new value is derived. Optionally, it can specify whether it wants to compress the value, which we discuss later in Section 3.3.1.

```
Put(key, base_version, value, compress) → version
```

When receiving the request, UStore creates a UNode object for the value and connects to the base object. A new version number is returned so that the application can retrieve this value later. The most important advantage of this operation is high throughput, as no requests are blocked or aborted. Since requests with the same base version will result in multiple branches, no locks are required and thus many requests can be served at the same time.

To retrieve a value, the application supplies both a key and a version number in order to identify the unique data version.

```
Get(key, version) → value
```

UStore first locates the target UObject based on the key, then it returns the corresponding UNode value for the given version. Note that this operation is also non-blocking, as existing versions are immutable and available for reading all the time. UStore provides no APIs for getting all the latest versions of a key, i.e., the versions without any successors. This is our design choice to minimize the overhead incurred by consistency mechanisms when there are concurrent updates. Nevertheless,
we provide an option for the application to receive notifications of updates via a publish/subscribe channel.

To merge two branches, we rely on the applications to specify merge semantics (discussed later), and only pass the consequent merged value to the storage.

\[ \text{Merge}(\text{key}, \text{version}_1, \text{version}_2, \text{merged}_\text{value}) \rightarrow \text{version} \]

UStore handles this operation similarly to a Put operation, but creating two connections to the two base UNode objects. Data immutability is not affected by \text{Merge}, since the operation creates a new version for the merged value.

To track previous versions or values of a given UNode, the application can invoke:

\[ \text{GetPreviousVersion/Value}(\text{key}, \text{version}) \rightarrow \{\text{versions/values}\} \]

which returns a single version/value of the current UNode as derived from a put operation, or two versions/values if it is derived from a merge operation. For example, in Figure 2 given \( v_8 \), this operation returns \( v_7 \), and given \( v_5 \) it returns \( \{v_2, v_4\} \). When receiving this request, UStore first locates the current UNode using the given version, then follows the backward connections to fetch the previous objects. By invoking this operation repeatedly, the application can trace the full history of the UObject.

To avoid calling GetPreviousVersion/Value many times, the application can use a batch operation that retrieves up to \( m \) previous UNodes.

\[ \text{GetKPreviousVersion/Value}(\text{key}, \text{version}, m) \rightarrow \{\text{versions/values}\} \]

UStore first locates the current UNode object, then recursively fetches the previous object, stopping when one of two following conditions occurs: when it reaches \( m \) hops away from the original requested object, or when it encounters a merged object. When the operation returns \( m \) objects with versions \( \{v_1, v_2, ..., v_m\} \), it means that \( v_i \) is the predecessor of \( v_{i-1} \), \( v_1 \) is the predecessor of version, and there are no branches in between. When it returns \( m' < m \) objects, it means there is a branch at \( v_m' \). Using this information, the application can determine which branch to follow next. For example, GetKPreviousVersion(\( k, v_8, 3 \)) returns \( \{v_7, v_2, v_1\} \), whereas GetKPreviousVersion(\( k, v_9, 3 \)) returns \( \{v_6, v_5\} \).

### 3.3 Physical Layer

We now describe how UStore implements the abstraction above at the physical layer. Our current design assumes all data is kept in memory, and support for migration to secondary storages is part of future work.

#### 3.3.1 UObject storage and indexing

There are two strategies to materialize UObject’s content: complete or incremental. In the former, UObject objects are stored in their entirety. In the latter, each object contains only the compressed data (e.g., the delta, which is the \text{diff} with its previous version), thus significantly reducing the storage consumption for a large UObject. However, there is a trade-off between the storage consumption and computation cost to reconstruct the objects. Thus, for the incremental strategy, in order to avoid traversing a long path to get a complete value, UStore allows the application to specify whether it wants to compress or not at each step. In addition, the application can register its specific \text{compress()} and \text{decompress()} functions based on their own data characteristics, which will be used by UStore during the compression and de-compression processes. As a result, UStore is flexible enough to achieve a variety of compression strategies. In UStore, the value is compressed based on its previous versions only if its previous version is local and is uncompressed. Otherwise, it will be based on its nearest uncompressed ancestor within the same node. The locality-aware partitioning scheme (discuss later), makes it highly possible that the previous version is located in the same node. We do not choose to compress the data based on a compressed one, because this will increase both the compression and de-compression cost.

As a UNode is uniquely identified by its key and version, we adopt a simple hash-based indexing to quickly locate the object with \( O(1) \) complexity. The \text{Put}(k, v_p, o) \) generates a new UNode version number as follows:

\[ v = (v.h, v.l, v.n) = (H(k|v_p|h|v_p,l||o), v_p,l + 1, \eta) \]  

where \( H \) is a cryptographic hash function and \( \eta \) a random value generated by the storage node. The version generated by \text{Merge}(k, v_1, v_2) \) is similar, except that \( v.l = \max(v_1.l, v_2.l) + 1 \). This means a merged object will be on the longest branch of its two ancestors, for example in Figure 2, \( v_5.l = 3 \). \( H \) ensures that version numbers are verifiable because both the content and link to the previous version are used to compute \( v.h \). It also ensures uniqueness: for any two inserts \( v_1 \leftarrow \text{Put}(k, v_p, o), v_2 \leftarrow \text{Put}(k', v_p', o') \) such that \( (k, v_p, o) \neq (k', v_p', o') \), then \( v_1 \neq v_2 \).

#### 3.3.2 Locality-aware partitioning

UObject granularities and volumes may vary considerably, for instance from large numbers of small objects as in a database application, to small numbers of large objects as in a Git-like application. In order to scale out to many nodes, we need to distribute UObjects evenly to multiple storage nodes, which can be achieved by hashing the key. The challenge, however, is in partitioning
a single, large UObject to multiple nodes, as shown in Figure[2]

One approach to achieve load balancing is to distribute UNode objects based on their versions using consistent hashing. Specifically, a version \( v \) is first hashed to identify the storage node, then it is used to index into the node’s local hash table. However, this approach fails to preserve locality: if \( v_2 \) is derived from \( v_1 \), the probability of both being in the same node is the same as that of any two random versions. Figure[2] shows an example of locality-preserving partitioning schemes which distributes related objects together onto the same node. Note that locality hashing schemes are not useful in our case, because the way we compute version numbers using a cryptographic hash function (Eq. [1]) destroys the relationship between two related versions. Instead, UStore achieves this property by generating versions using additional inputs from the storage nodes.

For each UObject, each server reserves a memory region \( t \) for storing its UNodes. The application can adjust \( t \) dynamically to better suit its storage requirements\[^1\]. For a write request, i.e. Put(\( k,v_p,o \)) where \( v_p = (v_p,h,v_p,l,v_p,n) \), the application uses \( (k|v_p,n) \) to locate a storage node \( S \) via consistent hashing, and routes the request to \( S \). The node \( S \) handles the request as follows:

- If its reserved memory region for the UObject is not full, it stores the object and returns a SUCCESS status, together with a new version \( v = (H(k|v_p,h)|v_p,l|o),v_p,l+1,v_p,n) \).
- When the reserved region is full, it generates a random value \( \eta \) such that \( (k|\eta) \) maps to a different region in the consistent hashing space. It returns a REDIRECT status and \( \eta \) to the application.

When the application receives a REDIRECT, it repeats the write request, but using \( (k|\eta) \) for consistent hashing, until it gets a SUCCESS response. The application can ask the server to increase \( t \) after a pre-defined number of redirected request. In one extreme, for example, the application may want to ensure all the write operations where \( v_p = vNNULL \) (root versions of top-level branches) result in the data being stored in the same node. In this case, when REDIRECT is returned, it asks the server to increase \( t \) immediately instead of following the redirection.

This protocol ensures object locality, because an write operation based on version \( v_2 \) implies the new object has derivation relation with \( v_p \), and its first priority of storage node is the same as that of \( v_p \). Only when the node exhausts its capacity is the object spilled over to another node. Unlike the common load-balancing approach in distributed hash tables which uses redirection pointers, UStore returns a new mapping in the form of \( \eta \), thus future requests are routed directly to the new node. In particular, a read operation, i.e. Get(\( k,v \)), proceeds by forwarding the request to the storage node identified via consistent hashing of \( (k|v,n) \). The node finds the object indexed by \( v \) and returns the object. By being able to adjust \( t \), the application has full control of how to balance the workload.

3.3.3 Caching and replication

The locality afforded by UStore’s partitioning does not help when objects are in different nodes. For example, given the objects in Figure[2], the request GetKPreviousValue(\( k,v_5 \)) incurs 3 network requests sent to 3 different servers. UStore provides a caching layer, that is each server maintains a cache of remote objects fetched during scan operations. In our example, \( v_2 \) and \( v_4 \) are cached at the same node of \( v_5 \), thus the next request for immediate predecessors of \( v_5 \) can be returned right away. By exploiting temporal locality of scanning operations, the server can answer requests more quickly. The cache is simple to maintain, since there is no cache coherence problems with immutable objects. For each UNode object, the server caches up to 2 remote predecessors, because the benefit of caching diminishes with increased number of cached predecessors.

UStore replicates UNode objects to achieve scalability and fault tolerance. Neighboring nodes in the consistent hashing space are replicas of each other. Replication is controlled by two parameters: number of replicas \( N \) and a write set size \( W \). Figure[4] illustrates the workflow for write and read requests (for simplicity, we assume that all inserts return SUCCESS). During a write operation, the Put request is sent to all the replicas in parallel, and it returns once there are acknowledgements from \( W \) servers. Note that \( W \) guarantees that the data is available when there are no more than \( W \) failures during the write operation. For a Get operation, the request is sent to the replicas in turn until the requested data is returned.

It can be seen that \( W \) balances the cost of read and write requests: larger \( W \) increases write latency, but may reduce read latency with high probability. On the other hand, larger \( W \) means less availability for write operations which only succeed when there are fewer than

\[^1\] via an out-of-band protocol

\[ \text{Figure 4: Workflow of write and read request} \]
(N – W) failures, but increased availability for read, as there are more replicas with the data. We note that there is similarity between UStore’s replication scheme and Dynamo’s [25] which is configurable by two parameters W and R. UStore does not require specifying R (or in fact, in UStore R = 1), because there is no read inconsistency in our system, thanks to the data being immutable.

3.4 View Layer

This layer enhances the immutability semantics of the layers below with fine-grained access control, data security. It increases the system’s flexibility by adding a notification service and an application hook for pushed-down merge semantics.

3.4.1 Access control and data security

UStore enables fine-grained access control at UObject level, allowing users to specify policies concerning specific UNode objects. The current design supports only read policies, and it assumes that storage servers are trusted, that users are authenticated (Section 6 discusses the challenges in supporting more expressive policies with stronger trust models). By default, UObjects are readable by all users. For a private UObject, UStore maintains a shadow object, called, ACUObject, with the same key. The ACUObject contains policies of the form (user id, list of versions), indicating which users can read which versions of the associated UObject.

Only the owner of the UObject can update its corresponding ACUObject, using the extended Put API. The ACUObject is stored at the same server with the versions being protected. When receiving a read request for some local versions, the server scans the local ACUObject for a policy granting access to the versions, before returning them to the user. Each new policy results in at most N ACUObjects where N is the total number of servers storing the associated UObject. This overhead can be mitigated by batching multiple policy into the same update. We also note that the number of policy updates in UStore is smaller than in other systems with mutable states, being protected. When receiving a read request for some local versions, the server scans the local ACUObject for a policy granting access to the versions, before returning them to the user. Each new policy results in at most N ACUObjects where N is the total number of servers storing the associated UObject. This overhead can be mitigated by batching multiple policy into the same update. We also note that the number of policy updates in UStore is smaller than in other systems with mutable states, because there is no need for revocation (once read access is granted to a version, it is considered permanent).

UStore protects integrity of both the data and of the version history against untrusted servers. Specifically, the version number is computed via a cryptographic hash function over both the data content and previous version number (Eq. 1), thus it is not possible for the untrusted server to return different data (for Get operations) or different predecessors (for GetPreviousVersion/Value operations). We consider two update operations with the same data and the same base version to be duplicate, and therefore it is safe to return the same version. For stronger guarantees, each server can also generate signatures for successful Put operations that can be used as proof of data storage.

3.4.2 Consistency model

Many distributed storage systems adopt the eventual consistency model: they allow reads to see stale values. However, reasoning about the returned value of a read is difficult in this model, because it depends on a multitude of factors: the concurrency model, the read-repair protocols, etc. In UStore, there are no stale reads, since every Get operation is specific to a version which is unchanged. There are only two possible outputs of a read operation: the correct value, or an error. The error indicates that the version has not been propagated to this replica, thus the request should be retried later. This semantics is clean and simple, making it easy to reason about the system’s states and correctness. Write operations in UStore are highly efficient for two reasons. First, once a UNode is written, it does not have to be sent immediately to other replicas. Second, concurrent writes to the same object in UStore have no order, therefore they require no locks and can be executed in parallel.

**Merge semantics.** Applications built on UStore must explicitly deal with conflicting branches caused by concurrent writes. UStore supports branch reconciliation via a function which merges two branches together. Specifically, the function \(m_{\text{merge}}(v_1, v_2, f_m)\) takes as input two version \(v_1, v_2\) belonging to two branches, a user-defined function \(f_m\), and generates a merged value defined by \(f_m\) (if successful). Our current design uses 3-way merge strategy, although we note that there exists several alternatives. This merge function first finds the closest ancestor, say \(v_0\), to both \(v_1\) and \(v_2\). \(v_0\) is where the two branch containing \(v_1, v_2\) forked. Next, it invokes \(f_m(v_0, v_1, v_2)\) to perform 3-way merge, which returns a value \(o\) if successful. Finally, it calls the lower-layer function \(\text{merge}\) to write a new version to UStore.

We observe that different applications may follow different logics when merging branches, and user’s intervention maybe needed because the conflict cannot be resolved automatically. For example, in Ficus [57], two versions adding two files to the same directory can be merged by appending one file after another. In Git, versions that modified two different lines can be merged by incorporating both changes, but if they modified the same line the merge should fail. UStore allows an application to define its own function \(f_m(\cdot)\) and use it when initializing the store. There is a number of pre-built functions in UStore, such as append, aggregation and choose-one.
3.4.3 Notification service

Recall that UStore does not provide APIs for retrieving the latest UNode objects. The main reason for omitting these APIs is to keep the storage semantics simple and clean. Under replication and failure, reasoning about the latest version is difficult, since the APIs may return different results for the same two requests. However, the need to track latest versions is essential to many applications, but we also note that many applications do not require real-time notification, hence they are tolerant of notification delays. One example is the collaborative analytics application in which collaborators need to be aware of each other’s updates in a timely manner, but not necessarily in real time, in order to avoid repeating work and complex conflicts.

To enable version tracking, UStore provides a notification service to which applications can subscribe. The service is essentially a publish/subscribe system in which the storage servers are the publishers and applications are the subscribers. It maintains pairs of events and application IDs, and is responsible for routing the events to the appropriate applications. When an application wishes to be informed of new versions of a UNode, it invokes register(,) function with its ID and the key of interest. When there is an update to the UNode, the storage server creates a new version and invokes publish(,). The service receives the new version and routes it to the registered subscribers. Our current design uses Zookeeper for this service, but we are adapting the design of Thialfi [11] to make the service more scalable.

4 UStore Applications

In this section, we present our implementations of four applications on top of UStore. They are a mix of established and emerging applications that exploit UStore’s core APIs to achieve high performance while reducing development effort.

4.1 Git

There are four main types of data structures in Git: Blob which contains unstructured data (e.g., text or binary data); Tree which contains references to other blobs and trees; Commit which contains meta data for a commit, i.e., commit message, root tree reference and previous commit reference; and Tag which contains tag name and commit reference. These data types are managed in a key-value store as records, and object references (i.e., keys of an object record) are explicitly recorded in the content. As a result, to extract references, the whole record has to be fetched and de-serialized. In UStore, we can easily separate history-based references (e.g., previous commit of a commit) from content-based references (e.g., blobs in a tree) since the storage’s version tracking naturally supports history-based references. We discuss here a simple version of Git implemented in UStore, providing the same properties as the existing implementation. We refer readers to the Appendix for an extension of this design that provides richer functionalities, such as file-level history tracking.

The original Git implementation supports contentaddressable storage by identifying an object by the cryptographic hash of its content. In UStore, version numbers can readily be used to uniquely identify objects. We maintain one UNode for each data type T which then manages all objects of that type. Fetching an object with a hash content h can be done via Get(T,h). Similarly, to commit a new version with content o, we use Put(T,NULL,o), which returns a deterministic and unique version. Since the version number can be precomputed, we can check if the version exists before committing. Note that when writing a Commit object to UStore, the previous version is tracked implicitly, enabling fast traversal of the commit history. Other Git commands, such as checkout, branch and merge can be implemented directly on top of these two fetch and commit primitives.

One benefit of using UStore is the ability to separate content and history references, making it more efficient to implement commands like git log. Furthermore, we no longer need to fetch the whole repository to check out a specific version, which is inefficient for repositories with long histories. Another benefit comes from UStore’s flexibility to support customized compression functions which can be more effective than the default zlib function. Our implementation totals 289 lines of C++ code. As a reference, the Git codebase adds up to over 1.8 million lines of C code (but it supports many more features than our UStore based implementation).

4.2 Collaborative Data Science

It is becoming increasingly common for a large group of scientists to work on a shared dataset but with different analysis goals [52][15]. For example, on a dataset of customer purchasing records, some scientists may focus on customer behavior analysis, some on using it to improve inventory management. At the same time, the data may be continually cleaned and enhanced by other scientists. As the scientists simultaneously work on the different versions or branches of the same dataset, there is a need for a storage system with versioning and branching capabilities. Decibel [15] is one of such systems that supports relational data model. We implement an application on UStore for the same collaborative workflows supported in Decibel.
Like Decibel, we provide two storage strategies for versioned relational databases, namely Tuple-First and Version-First. In the former, we treat tuples from different tables and versions the same. Specifically, a tuple is stored as a TObject, where the key is the tuple’s primary key and the different versions of the tuple correspond to the TObject objects. To realize the relational model, we use another type of TObject to maintain the tuples’ membership to tables and versions, where the key is the table name and version, and each TObject stores a bitmap index to track whether a tuple is present in the versioned table. In the Version-First strategy, tuples from one versioned table are stored in a single TObject object. We support large numbers of tuples by storing them with two-level paging. More specifically, in the first level, the TObject’s key is the table name and version, while its value contains a set of keys of the second-level TObjects which actually store the tuples.

There are two advantages in our UStore-based implementation compared to Decibel. First, UStore stores tuples in memory instead of on disk, thus the operations are faster. Second, it can be scaled out easily to support large datasets, whereas Decibel is currently restricted to a single node. Our implementation amounts to 640 lines of C++ code (as a reference, the Decibel’s codebase adds up to over 32K lines of Java code).

### 4.3 Transaction Management

TARDiS[21] is a branch-and-merge approach to weakly consistent storage systems. It maintains a data structure called state DAG to keep track of the database states as well as the availability of data versions to any transaction. Unlike Git which creates branches explicitly on demand, TARDiS generates branches implicitly upon conflicts of data accesses. By doing so, TARDiS can keep track of all conflicting data accesses in branches. Like UStore, it enables flexible conflict resolution by allowing the high-level application to resolve the conflicts based on its own logic.

In TARDiS, a transaction $T$ issued by client $C$ starts by searching the state DAG for a valid state that it can read from. A state is valid when it is both consistent and compatible to $C$’s previous commits. It could be a state that is previously created by $C$ or whose ancestor state is created by $C$. Once a read state is selected, denoted as $S_T$, the transaction can perform read operations by referring to $S_T$. Specifically, when reading an object $O_w$, it checks all the versions of $O_w$ in the storage starting from the latest version, and greedily finds the version (identified by the corresponding state which created it) that is compatible with $S_T$. Here, compatibility means that the version $T$ is reading must be in the same branch with $S_T$. When writing an object $O_w$, the transaction creates a new version of $O_w$ based on the transaction identifier. When committing, it checks whether $S_T$ is still valid. As long as $S_T$ is valid, $T$ will eventually commit (e.g., commit after the $S_T$ in the state DAG). Because other concurrent transactions may not have conflicts with $T$ in terms of updates, it ripples down from $S_T$ to find and commit after the deepest compatible state.

The structure of state DAG in TARDiS can be mapped directly to UStore. In fact, we implement TARDiS in UStore by simply using TObject to store the states. This implementation, referred to as TARDiS+UStore, leverages UStore’s efficient version scan operation to carry out backward search from the latest DAG states. When data accesses are skewed, there is a high probability that data read by a transaction is updated in a recent state. Therefore, searching for data versions by backtracking (as in TARDiS+UStore) is more efficient than by scanning the topologically sorted version list for each data item (as in TARDiS). Our implementation adds up to 1068 lines of C++ code (there is no open source version of TARDiS, so we implement both systems from scratch).

### 4.4 Blockchain

A blockchain is a decentralized shared ledger distributed among all participants of the system. Data immutability and transparency are two key properties that fuel the recent rise of blockchains. Figure illustrates a typical blockchain data structure, where the data is packed into a block that is linked to the previous block, all the way back to the first (genesis) block, through cryptographic hash pointers. If the data is tampered in any block, all hash pointers in the subsequent blocks become invalid. In a blockchain network, the participants agree on a total order of transactions, i.e., a unique evolution history of the system states. In some blockchain systems, like Bitcoin[50], the blocks keep no account state (e.g., balance), but only the unspent crypto-currencies (or coins). In other systems such as Ethereum[30], the account states are stored explicitly in the blocks as shown in Figure[3].

We implement a blockchain data structure similar to Ethereum using UStore, in which we maintain the account states inside the blocks. There are two layers of
data in our design, namely a block layer and an account layer. In the block layer, each block contains metadata, such as the proposer of this block, the root hash of account list, etc. It is stored as a UNode object whose key is the same for every block. When we append a new block (using Put), we use the version of its preceding block as its base version. This way, UNode’s version numbers become the hash pointers of the blockchain. In the account layer, each account object, stored as a UNode, keeps track of the account balance, where the UNode’s key is the account address.

Existing blockchain systems still lack an efficient and scalable data management component, which also helps enhance the security and robustness of the blockchain. For instance, the recent DDoS attack on Ethereum is attributed to inefficiency in fetching state information from disk. A new blockchain built on UStore can benefit directly from the scalability and efficiency of the storage. Moreover, by exploiting UStore’s versioning capabilities, the new blockchain system can support efficient analytical queries which are useful for gaining insights from the data in the blockchain. We implemented the blockchain logics on UStore using 1,231 lines of code in C++. As a reference, the popular Ethereum client (Geth) comprises 539,584 lines of Go code.

5 Evaluation

In this section, we report the performance of UStore and of the four applications discussed above. We first evaluate UStore’s data access operations (read, write and version scan) and compare them against Redis. The results show that UStore achieves comparable performance with Redis for basic read and write operations. By exploiting locality-aware partitioning, UStore achieves 40x lower latency than Redis for scan operations. We also examine the performance trade-off against availability and compression strategies, which can be controlled by the applications. Next, we evaluate four UStore-based applications against systems supporting the same operations. The Git-like application improves commit and checkout latency by up to 240x and 4000x respectively, thanks to data being stored in memory and the simplicity of the checkout operation. The collaborative data science application achieves up to 10x better latency in 3 out of 4 queries, due to the in-memory design. The transaction management application reduces the number of states accessed by up to 80x for skewed workloads by leveraging the efficient scan operations. Finally, for blockchain application, UStore’s datastructure matches well with blockchain data, and the system’s efficient data access operations account for up to 400x lower latency in 4 out of 5 queries.

All experiments were conducted in a 20-node, RDMA-enabled cluster. Each node is equipped with a E5-1650 3.5GHz CPU, 32GB RAM, 2TB hard drive, running Ubuntu 14.04 Trusty. There are two network interfaces per node: one 1Gb Ethernet, and one Mellanox 40Gb Infiniband.

5.1 Microbenchmark

Basic operations. We ran the YCSB benchmark to measure UStore’s read and write operations and compare them against Redis (v3.2.5 release). To support pure key-value workloads (without versioning), we replace UStore’s default hash function with another that ignores version numbers when locating the objects. Figure 6 shows the throughput for a varying number of clients over the workload with 50/50 read and write ratio, each client using 64 threads. Without RDMA, UStore’s performance is comparable to Redis’s. With a single client, Redis achieves higher throughput, at 86K operations per second (Kops), than UStore does at 60 Kops. This is due coarse-grained locks implemented at UStore clients (future optimization will likely improve the current client throughput). However, with more clients, Redis server becomes saturated and UStore performs slightly better. The performance gain is due to multi-threaded implementation of UStore, as opposed to Redis’ single-threaded implementation. Using RDMA, UStore achieves much higher throughputs, which is as expected because of the high bandwidth and efficient networks. In particular, the RDMA version requires 8 clients to saturate it at 430 Kops, whereas Redis is saturated by 4
clients at 110 Kops. We note that this gap could be eliminated when Redis includes native support for RDMA.

Scan operations. Next, we considered version scan operations which are common in many applications. Given a version \( v \) and value \( m \), the query returns \( m \) predecessors of \( v \), assuming a linear version history. This is supported directly in UStore by the \texttt{GetKPreviousValue/Version} APIs. We implemented this operation in Redis for comparison, in which we embedded the previous version number into the value of the current version. Figure 7 illustrates the differences in latency between UStore and Redis. With increasing \( m \), Redis incurs an overhead growing linearly with \( m \), since it must issue \( m \) sequential requests to the server. On the other hand, the number of requests in UStore is constant since the server can send up to \( m \) versions back in one response. Since each request involves a network round-trip, the query latency at \( m = 32 \) is much lower in UStore, at 0.4ms (and 0.07ms with RDMA), than in Redis (over 3ms).

Performance trade-offs. We benchmarked UStore’s various performance trade-offs by examining its performance with different values of \( W \) and different compression strategies. We briefly explain the findings here, and refer readers to the Appendix for the detailed results and analysis. We observed that increasing \( W \) leads to slower writes, but it has no impact on read latency. Furthermore, our default compression strategy outperforms a random compression strategy, and achieves a good balance in terms of throughputs and memory consumptions as compared to a no-compression strategy.

5.2 Git

We evaluated our UStore-based Git implementation (referred to as UStore) against the original Git in two data-versioning related operations, i.e. checkout and commit. We measured both implementations in terms of operation latency and storage consumption. First, we generated a synthetic workload containing varying numbers of data versions. Each version consists of a single fixed-size (32KB) file with random printable characters. For each commit operation, we overwrite the file with content of the next version, and commit it into Git or UStore. For Git, we use a practical work-flow for commits, in which each commit is first saved into a local repository (\texttt{git commit}), and then pushed to a remote server (\texttt{git push}) running GitLab. For UStore, we set up one server and have the client sending requests from a remote node.

Figure 8 shows the latency for checkout operations with varying repository sizes (number of commits). We refer readers to the Appendix for the results of commit operations and of the storage cost. For single-version checkout operations, Git is significantly slower than UStore (4000x), because the former requires the client to fetch the entire history even when only a single version is needed. The checkout latency in Git also increases with longer history, whereas UStore’s latency remains constant, because the latter fetches only one version. For the multiple-version checkout operations, we observe similar, but smaller gap. In this case, UStore’s latency increases linearly with the number of checkouts because each operation is independent, whereas in Git the initial cost of fetching the entire history is amortized over subsequent checkouts which are done locally.

To compare the cost of commit operations in UStore and in Git, we performed one commit operation with varying file size. We observe that UStore is up to 200x faster than Git, mainly due to Git’s overhead when pushing commits to the remote server. In particular, before connecting to server, Git triggers object packing — a time consuming process — that compressed multiple objects to save network bandwidth.

5.3 Collaborative Data Science

We evaluated Decibel against our implementation for the collaborative workflows (referred to as UStore) on a single-node setting, since Decibel does not support running on multiple nodes. We first populated both systems with a synthetic dataset similar to what was used in [45]. The dataset consists of 832,053 tuples, each has 10 integer fields with the first being the primary key. We used the science branching pattern, in which new branches either start from the head of an active branch, or from the head commit of the master branch. We set the page size in Decibel to 4MB. We considered four queries as in [45]. The first query (Q1) scans all the active tuples on master branch. The second query (Q2) scans all the active tuples on the master branch but not on another branch. The third query (Q3) scans all the tuples active on both the master and on another branch. The fourth query (Q4) scans all the tuples active in at least one branch. We implement these queries in UStore using the Version-First storage strategy.

Figure 9 compares the latency for the four queries.
UStore outperforms Decibel for the first three queries. The performance gain is due to the fact that UStore is memory-based, as opposed to Decibel’s disk-based storage backend. For example, UStore takes only 33ms to execute Q1, while Decibel takes 328ms. However, Decibel is better in Q4, because it implements optimizations based on branch topology and with which it can avoid redundant scanning of common ancestors of different branches. UStore has no such optimizations and therefore takes longer to complete a full scan. We also compared both systems with the Tuple-First storage strategy, and we observed that Decibel outperforms UStore in most cases. This is due to another optimization in Decibel where it can perform sequential access by scanning tuples in a single heap file for each branch, while UStore has to make many random accesses. We note that implementing these optimizations in UStore is non-trivial, hence we plan to include them as part of future work.

5.4 Transaction Management

To evaluate TARDiS+UStore against the original TARDiS, we used workloads consistent with what described in [21]. In particular, a read-only transaction performs 6 reads, and a read-write transaction performs 3 reads and 3 writes. We considered two types of workloads: read-heavy which contains 75% read-only transactions and 25% read-write transactions, and mixed which contains 25% read-only transactions and 75% read-write transactions. We set the number of concurrent clients to 1000 and generated random data accesses following the Zipfian distribution. We report here the total number of state accesses by the read operations. As the write operation is efficient in both implementations, the performance gap is determined by the efficiency of read operations whose performance is proportional to the number of state accesses.

Figure 10 shows the results for the mixed workload (those for the read-heavy workload are similar). It can be seen that when the skewness of data accesses is low (e.g., Zipf=0 which is equivalent to uniform distribution), TARDiS outperforms TARDiS+UStore. This is as expected, because TARDiS+UStore has to scan longer branches to find the versions. But when the skewness is high (e.g., Zipf=1.5), TARDiS+UStore shows clear advantages. This is because updates of frequently accessed data can be found in recent states, therefore backtracking involves small numbers of hops to locate the required versions. When the skewness grows even higher, the performance gap widens accordingly. In particular, when Zipf=2.5, the original TARDiS makes 80x more state accesses than TARDiS+UStore. These results demonstrate that our UStore-based implementation achieves better performance when data accesses are skewed, which is a common access pattern in real-world applications.

5.5 Blockchain

We compared UStore-based blockchain implementation (referred to as UStore) against Ethereum on queries related to blockchain data. We generated a synthetic dataset with 1,000,000 accounts in the genesis block, and 1,000,000 subsequent blocks containing 10 transactions per block on average. This dataset is consistent with the public Ethereum data. We deployed both US-store and Ethereum’s Geth client on a single node, and evaluated them over five queries. The first query (genesis block load) is to parse and load the genesis block into the storage to initialize the system. The second query (general block load) is to load all subsequent blocks into the storage. The third query (latest version scan) is to scan the latest version of all the accounts. The fourth query (block scan) is to scan the content of previous blocks from a given block number. The fifth query (account scan) is to scan previous balances of a given account at a given block. The last three queries represent the analytical workloads anticipated in the future deployment of private blockchains [49].

Table 2 summarizes the latency of the first three oper-

Table 2: Ethereum performance vs. UStore on block load and account scan

|                  | Genesis Block (sec) | General Block (ms) | Scan Accounts (sec) |
|------------------|---------------------|--------------------|---------------------|
| Ethereum         | 622.45              | 19                 | 1148.096            |
| UStore           | 175.516             | 35                 | 167.546             |

Table 2 summarizes the latency of the first three oper-

2https://etherscan.io/
Figure 11: Ethereum performance vs. UStore on account level version scan

ations in Ethereum and in UStore. Figure 11 shows the latency for the account scan query, in which UStore is up to 400x better (the results for block scan query are similar and included in the Appendix). It can be seen that UStore outperforms Ethereum on all operations except the general block loading operation. The performance gain is attributed to three factors. One factor is that UStore serves data from memory, and it leverages RDMAs. Another factor is that it uses an AVL variant to index the accounts, which has better performance for insertion than Ethereum’s Patricia-Merkle tree. But more importantly, UStore’s data structures are a better match for version oriented queries than Ethereum’s, and thus the application can directly benefit from the efficient version operations provided by the storage. For instance, UStore is better for the last two queries because of the efficient version scan operation. Furthermore, for the account scan query, Ethereum maintains no explicit pointers to the previous version of an account, thus it has to fetch and parse the content of a previous block before retrieving the previous account version. This process requires reading redundant blocks and therefore incurs more overhead. In contrast, UStore can leverage the GetKPreviousVersion/Value API to retrieve the previous versions directly. Ethereum is better for general block load query because it imports blocks in batches without verifying the content, whereas UStore imports one by one.

6 Discussion and Future Work

The current evaluation of UStore focuses only on the system’s core APIs. View-layer components, especially the access control and notification service, are still to be evaluated in isolation and as parts of the overall performance. Furthermore, the applications in UStore (except for the transaction management application) were compared against full-fledged systems which support many others operations beside what were implemented in UStore. In other words, we ported only a small number of features from these systems into UStore, ignoring many others that may contribute to the overall performance. Adding more features to these applications are part of future work.

Much of the future work, however, is to enhance the view layer. The current access control mechanism is restricted to read policies, and it assumes trusted servers. Supporting fine-grained write access is non-trivial, since the semantics of write access to a version needs to be formally defined, and the enforcement must be space efficient. Even for read policy, it remains a challenge to compactly represent a policy concerning multiple versions, since version numbers are random. The next step is to relax the trust assumption, for which we plan to exploit trusted hardware (Intel SGX) to run the enforcement protocol in the trusted environment.

A view-layer module that implements more advanced data models from the core abstraction can greatly reduce development effort. For example, our implementation of Git and collaborative applications require several levels of UObject in which one level stores pointers to another. Such grouping of low-level UObject into higher-level abstractions is useful to track provenance and changes application meta-data. Most applications we ported to UStore require more complex access to the data than the current Put and Get APIs. Thus, we plan to implement a query and analytics engine as a view-layer module to support rich operations over the immutable data. Other interesting modules that enrich the view layer include utility modules that support authentication and integration with existing systems (like a big-data pipeline or a machine learning system).

The current physical layer is designed for data-center environments. Extending it to non-cluster (decentralized) settings requires addressing two challenges: disk-based storage management (garbage collection), and data management in the presence of churn. At the other end of the stack, we note a recent rise of big meta-data systems. As more systems are being built around interactions with human experts to extract contextual intelligence, capturing the context of such interactions is crucial for improving the systems. Furthermore, as machine learning models are becoming important for decision making and system tuning, understanding their provenance is an important step towards better interpretation of the models. Ground and Goods are two meta-data systems focusing on extracting and managing data context, especially data provenance. One central component in Ground is the immutable, multi-version storage system, which the authors demonstrated that existing solutions fall short. UStore can be an integral part in such systems, and consequently serve the emerging classes of applications based on meta-data.

3https://github.com/tendermint/go-merkle
7 Conclusion

In this paper, we identified three properties commonly found in many of today’s distributed applications, namely data immutability, sharing and security. We then designed a flexible, efficient and scalable distributed storage system, called UStore, which is enriched with these properties. We demonstrated how the new storage adds values to existing systems and facilitates faster development of new applications by implementing and benchmarking four different applications on UStore.

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Figure 12: Blockchain software stack

A UStore Applications

A.1 Advanced Git Application

The simple Git implementation described in Section 4 only tracks version history at commit level as in original Git protocol. To extend this, we target to track histories for all data types, especially blob (file) and tree (folder). The immediate benefit is that users can view change list of a file or folder more quickly.

To achieve this, we need to separate files and folders as different UObjects, using their name as keys and serialized content as value. When we detect that the content has changed during a commit, (e.g., same file name but different content as in previous checkout) we invoke $\text{put}(\text{name}, \text{version}, \text{content})$.

The merge operation for two versions is similar. After resolving conflicts and generating the merged content, we invoke $\text{merge}(\text{name}, \text{version}_1, \text{version}_2, \text{content})$. This returns a version id which can be used to fetch that object.
A.2 Blockchain

We only described the data structure of blockchain in Section 4.4 but a typical blockchain system consists of many more complex components besides the data storage. Here we elaborate a typical architecture of a blockchain system as shown in Figure 12.

Many applications such as cryptocurrencies, digital asset management and financial security settlement can be built upon blockchains. Typically, some of the nodes in a blockchain network may exhibit Byzantine behavior, but the majority is honest, thus, the nodes have to reach agreement on the unique evolution history of the global system state through a consensus protocol (e.g., PBFT in Hyperledger[35], PoW in Bitcoin[50] and Ethereum[30]). To be general and extensible, recent blockchain platforms, like Ethereum and Hyperledger, support smart contract functionality that allows users to define their own transaction logic and develop their softwares called decentralized application (DApp), e.g., decentralized online money exchange. The smart contracts are usually written in Turing-complete languages and executed in an isolated execution environment provided by the blockchain, such as Ethereum Virtual Machine (EVM) of Ethereum. Because the nodes in blockchain network cannot be fully trusted, blockchain platforms usually construct validity proofs based on Merkle hash tree and its variants that are also used as the indexes for system internal states.

Although the storage engine is only a part of the complex blockchain software stack, there is a need for efficiency and scalability which is critical for smart contract execution and historical data audit. As we shown in our experiment, UStore can serve as the data store of choice for high performance blockchains.

B Experimental Results

B.1 Microbenchmark

Figure 13 shows the latency for read and write operations with 4 clients. It can be seen that UStore can achieve 3x lower latency thanks to RDMAs. Even without RDMAs, UStore is slightly better than Redis, because our server is multi-threaded. Another source of overhead can be due to Redis’ support for complex data types such as lists and sorted sets, whereas UStore supports simple, raw binary format.

Figure 14 illustrates UStore’s performance with varying number of write replicas W. For this experiment, we run 4 UStore nodes and set N = 3. Recall that W determines how many responses from the replicas are needed before a write operation is considered successful. As a result, higher W leads to higher latency for writes, as we can see for write-heavy workloads in Figure 14. W only affects read operations in the extreme cases where a read request is sent immediately after the write request to a replica which has not finished writing the data, which is rare in our cases. Thus, we observed no impact of W on read-heavy workloads.

Compression strategies. We benchmarked the effect of our compression strategy, by comparing it with the no compression strategy and a random compression strategy, where we randomly select an ancestor based on which we do the compression, in terms of both the...
performance and memory consumption. We generated two workloads with 1.6 M records of 1 KB length and long version traces, i.e., a delta workload (DW) where the current version is generated based on its previous version with some delta changes, and a randomly generated workload (RW) where every version is generated randomly. We used 2 servers and 16 clients. The results are shown in Figure 15. We can see that under the delta workload (DW), our compression strategy saves a lot of memory space, but only performs partially worse than the no compression strategy, while under the random workload (RW), their memory consumption is similar, because there is no much opportunity for effective compression under random workload (RW). The random compression strategy performs worst, in terms of both memory consumption and performance under both workloads, which is mainly due to the high probability of network communication during the compression and de-compression, and it does not take advantage of the fact that only neighboring versions are likely to have similar content (i.e., there are overlooked opportunities for effective compression).

B.2 Git

Figure 16 illustrates the cost for committing a file into Git versus into UStore. It can be seen that the commit operation in UStore is up to 200x faster than in
Git. This performance gap is attributed to several factors. First, UStore stores data in memory which avoids external I/Os. Second, Git incurs much overhead when pushing commits to the remote server. Before connecting to server, Git automatically triggers object packing to combine multiple objects as compressed packages. This strategy reduces network communication, but it is time consuming.

Figure 17 and Figure 18 show the storage space consumption for maintaining a Git repository at the server side. In order to reduce space consumption, Git uses zlib to compress all objects, reducing both storage and network cost. We conducted a test with plain text workload. As shown in Figure 17, Git occupies less space than UStore, since we do not apply any compression in UStore. However, UStore exposes the interface for users to define own compression strategies, e.g. zlib. More importantly, compression in UStore can be application-specific. Users can leverage unique characteristics of their data to perform much better. For example, we generated an AES encrypted workload, which is ineffective to compress directly. We then injected a customized compression function into UStore which processes the data in decrypt-compress-encrypt manner. Figure 18 validates the effectiveness of this application-specific compression. We can see that if users know their data well, it is easy for UStore to outperform the default compression in Git.

### B.3 Blockchain Application

Figure 19 illustrates comparison between Geth and UStore on block level version scan operations described in Section 5.5. It shares a similar performance pattern with account level version scan operation shown in Figure 11 but incurs less overhead in Geth than account level version scan. This is because in Ethereum’s implementation, when scanning account versions, it has to fetch the block information corresponding to that account version as well.