Warp: Lightweight Multi-Key Transactions for Key-Value Stores

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Abstract

Traditional NoSQL systems scale by sharding data across multiple servers and by performing each operation on a small number of servers. Because transactions on multiple keys necessarily require coordination across multiple servers, NoSQL systems often explicitly avoid making transactional guarantees in order to avoid such coordination. Past work on transactional systems control this coordination by either increasing the granularity at which transactions are ordered, sacrificing serializability, or by making clock synchronicity assumptions.

This paper presents a novel protocol for providing serializable transactions on top of a sharded data store. Called acyclic transactions, this protocol allows multiple transactions to prepare and commit simultaneously, improving concurrency in the system, while ensuring that no cycles form between concurrently-committing transactions. We have fully implemented acyclic transactions in a document store called Warp. Experiments show that Warp achieves $4\times$ higher throughput than Sinfonia's mini-transactions on the standard TPC-C benchmark with no aborts. Further, the system achieves 75% of the throughput of the non-transactional key-value store it builds upon.

1 Introduction

NoSQL systems have become the de facto back-end for modern applications because they allow unprecedented performance at large scale. The defining characteristic of these systems is their distributed architecture, where the system shards data across multiple servers to improve scalability. To further improve scalability, these systems typically avoid cross-server communication, which makes it difficult to implement ACID transactions.

Yet, distributed transactions require coordination among multiple servers. In traditional RDBMSs, transaction managers coordinate clients with servers, and ensure that all participants in multi-phase commit protocols run in lock-step. Such transaction managers constitute bottlenecks, and modern NoSQL systems have eschewed them for more concurrent implementations. Scatter [21] and Google's Megastore [6] shard the data across different Paxos groups based on their key, thereby gaining scalability, but incur higher coordination costs for actions that span multiple groups, and require that operations on the same group be sequenced by the same Paxos instance. Google's Spanner [13] combines traditional locking techniques with a novel TrueTime API to provide fast read-write transactions, and lock-free reads. Many recent systems propose moving pieces of the transactional programs themselves to the server. Calvin [50] serializes all transaction inputs via a consensus protocol, and then deterministically executes application code on servers. Lynx [52] and Rococo [35] break down the transaction into multiple atomic fragments, and employ static analysis to detect opportunities for reordering the shipped code components. Both techniques rely upon a priori knowledge and analysis of the transactions.

This paper introduces Warp, a NoSQL system that enables efficient multi-key transactions with ACID semantics. Warp offers, to our knowledge, the highest degree of concurrency in a general purpose serializable NoSQL data store. Further, it achieves throughput far in excess of previous systems, approaching 75% of the throughput of the system on which it builds. The key insight that enables these performance improvements is a commit protocol called *acyclic transactions*, which allows the system to order transactions on-the-fly without any prior static analysis, and without moving code to the server.

Three techniques, working in concert, enable acyclic transactions to achieve its high scalability and performance. First, acyclic transactions reduce coordination costs by reducing the number of transactions that are ordered to the minimum necessary to enforce serializability. Transactions that operate on disjoint data or whose executions do not overlap in time will incur zero coordination costs. Warp orders only those transactions that concurrently operate on overlapping data, and does so

with minimal overhead.

Second, Acyclic transactions achieve scalability by arranging servers into data-dependent, dynamically-determined chains, where each chain contains, solely, those servers which store data affected by the transaction. This structure, avoids bottlenecks at transaction managers and improves performance by cutting communication costs.

Finally, acyclic transactions improve performance by allowing multiple overlapping transactions to proceed in parallel under the right conditions. Locking protocols inherently limits concurrency, while traditional optimistic two-phase protocols can only prepare one transaction per key at a time, because all reads must be validated in the first phase before the second phase may begin. In contrast, Warp enables multiple transactions to prepare simultaneously by taking advantage of the inherent serialization in its data-dependent chains.

Overall, this paper makes three contributions. First, we outline a novel protocol for providing efficient, onecopy serializable transactions on a distributed, sharded data store. Our protocol provides an unprecedented level of concurrency and scalability without any synchronicity assumptions or static analysis. Second, we describe our implementation of the commercially available Warp key-value store, including the design of the client. The system has been fully implemented and provides language bindings for C, C++, Python, Java, Ruby, Go, and Node.JS. Third, we show through macro- and microbenchmarks that Warp can provide higher throughput than alternative designs, with fewer aborted transactions. Specifically, Warp achieves a throughput that is $4\times$ higher, with $5 \times$ lower latency, than mini-transactions [2], the closest existing approach, on the TPC-C benchmark. The system achieves 75% the throughput of the underlying non-transactional key-value store upon which Warp builds.

The rest of this paper is organized as follows. Sections 2 and 3 describe the acyclic transactions protocol and our implementation of Warp. Section 4 evaluates the performance of Warp. Section 5 surveys existing systems and related work and Section 6 concludes.

2 Design

Warp builds upon the HyperDex [17] key-value store by modifying the existing components to provide transactional guarantees. Warp's architecture is based on HyperDex. To that end, Warp consists of three components: the coordinator, clients, and storage servers. The coordinator maintains the meta-state for the system, specifically, the partitioning of the key space across storage servers. Clients issue requests directly to the storage servers, where a request may affect a single object, or span multiple objects. Each storage server maintains a

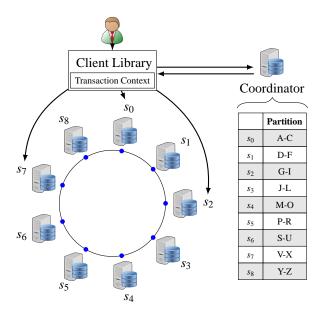


Figure 1: Warp's architecture consists of storage servers, the coordinator, and the client library. The coordinator maintains the partitioning of the key space across servers, and supplies this mapping to the client library. The client library uses this mapping to directly contact storage servers.

subset of keys in the system; collectively, the storage servers hold all data stored by the system. Figure 1 illustrates Warp's overall architecture.

The Warp client library provides isolation by optimistically performing read and write operations against local state, and verifying that this state remains the same at commit time. To perform a read, the library retrieves the requested data from the storage servers and caches the object within the local transaction's state, called the transaction context. Subsequent reads within the transaction will be satisfied by the transaction context, if possible. Write operations executed within the transaction are not visible on the servers immediately. Instead, they are saved to the transaction context to be written at commit time. Multiple writes to the same key will overwrite the locally saved object. Storage servers are unaware of any modifications written within a transaction until the client commits the transaction. To commit the transaction, the library submits the set of all objects read and all objects written to the storage servers using the acyclic transactions commit protocol.

2.1 Commit Protocol

The acyclic transactions commit protocol processes clients' transactions, and ensures that they either commit in an atomic, serializable fashion, or abort with no effect. The protocol does this for each transaction by simultaneously validating the values optimistically read by the

client library, and ordering the transaction with respect to other concurrently executing transactions. While it is relatively easy to validate a transaction by comparing the values observed by the client to the latest values in the data store, it is considerably more difficult to order transactions across multiple servers. The former is a local check that each server may independently perform during transaction processing, while the latter requires that multiple servers coordinate to agree upon the serializable order of transactions.

The key insight of the acyclic transactions protocol is to arrange the servers for a transaction into a chain, and to validate and order transactions using a dynamicallydetermined number of passes through this chain. Compared to traditional commit protocols which use fanout/fan-in communication patterns, acyclic transactions pass messages forward or backward between adjacent nodes in the chain. This ensures that there is at most one server actively processing each transaction at any one time. By limiting the parallelism present in a single transaction, acyclic transactions enable each server to locally make a binding decision about the fate of the transaction they are processing, and propagate that decision to the next server in the chain. Globally, this enables multiple transactions which modify the same data to execute in parallel—transactions whose execution other techniques would serialize—because each pair of concurrent transactions is ordered by exactly one server that can decide their order without communicating with other servers. Any decision made by a server will be carried to, and enforced by, the remaining servers in the chain.

The protocol consists of multiple distinct processes that work in concert to commit transactions. To commit the transaction, the client library determines the chain of servers which process the transaction's commit. These are only those servers that house the data involved in the transaction. The servers in this chain follow simple rules to commit the transactions: a server passes a transaction forward in the chain only when the server may commit that transaction; otherwise, the server sends either an abort or a retry request backward in the chain. Transactions will be aborted when they fail to validate the clients' reads, and will be retried to ensure the order between concurrent transactions is serializable. When the transaction passes completely through the chain in the forward direction, the last server in the chain finalizes the transaction by sending a commit message backwards through the chain. This commit message instructs servers to persist the transactions to disk, and to clean up any transient state related to the transaction.

2.1.1 Chain Construction

Clients use the transaction's context to construct a chain to commit the transaction. To ensure that servers process

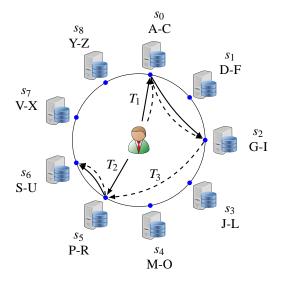


Figure 2: Clients deterministically construct dynamic chains based upon the keys read and written by transactions. In this example, a client submits T_1 , T_2 , and T_3 . Transactions T_1 and T_2 operate on disjoint keys, $\{k_A, k_H\}$ and $\{k_P, k_T\}$ respectively. T_3 touches all four keys and forms a chain that includes the chains of T_1 and T_2

transactions' operations in a predictable order, the client library sorts the keys read or written by a transaction in lexicographical order, and maps this sorted list onto a set of storage servers. Because sorting is a deterministic process, transactions with multiple keys in common pass through their shared set of servers in the same order.

Figure 2 shows how transactions that read and write the same keys have overlapping chains. Transaction T_1 reads key k_H and writes key k_A , while transaction T_2 reads keys k_P and k_T . Transaction T_3 writes keys k_A , k_H , k_P , and k_T . The object-to-server mapping dictates that T_1 's chain pass through servers s_0 and s_2 because these servers hold objects k_A and k_H respectively. Similarly, T_2 forms a chain through s_5 and s_6 . T_3 writes the same keys touched by T_1 and T_2 and has a chain that passes through the same servers as transactions T_1 , and T_2 .

Constructing chains in this way makes it straightforward to order transactions that concurrently operate on the same data. The first server in common between two transactions' chains can order any two overlapping transactions, and notify all subsequent servers in both chains. The mapping maintained by the coordinator ensures that transactions with data in common will pass through a common set of same storage servers, even when the mapping is updated to reflect system membership changes. Inversely, when two chains do not overlap, there is no need to directly order their transactions, because they necessarily operate on disjoint data.

2.1.2 Validation

The validation step ensures that values previously read by the client remain unchanged until the transaction commits. To do this, servers ensure that the value the client read during its transaction is the same value currently in the data store, and that no concurrent transactions change the value that the client read. Specifically, servers check each transaction to ensure that it does not read values written by, or write values read by, previously validated transactions. Servers also check each value against the latest value in their local store to ensure that the value was not changed by a previously-committed transaction. Thus, acyclic transactions employ optimistic concurrency control [26, 49].

Servers perform validation for each transaction before forwarding it to subsequent servers in the chain. This ensures that at any step in a transactions' processing, a prefix of the chain guarantees that the transaction is valid and will remain valid until the transaction commits or aborts. Storage servers will abort subsequent transactions whose writes would invalidate previously valid transactions. Consequently, when a transaction reaches the last server in the chain, that server can decide to commit or abort the transaction without consulting any other server—the protocol guarantees to the server that every previous server will be able to commit the transaction.

When a server determines that a transaction does not validate, the server aborts the transaction by sending an abort message backwards through the chain. Each server in the prefix aborts the transaction and forwards the abort message until the message reaches the client. These servers remove the transaction from their local state, enabling other transactions to validate in its place.

2.1.3 Ordering

The central task of the acyclic transactions protocol is to establish a serializable order across all validated transactions. While the protocol could simply serialize all transactions—which would maximize spurious coordination—it instead relies upon the observation that a set of transactions are serializable if the dependency graph of their relative orders is free of cycles. Each edge in this graph specifies a pair of transactions and the relative order between them. We refer to the transactions at each endpoint of an edge as a *conflicting pair*, because one transaction contains a write operation on a key which was read or written by the other. Consequently, every conflicting pair has at least one, and possibly several, keys that are common to both transactions.

The difficulty in ordering these conflicting pairs lies not in resolving pairwise relationships, but in ensuring that every pairwise ordering is consistent with the globally serializable order. Resolving the order across multiple pairs is a considerably more complex task, be-

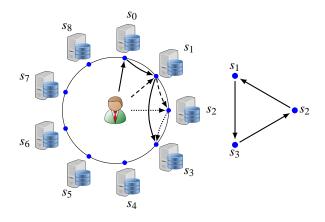


Figure 3: Ordering transactions in a serializable fashion across multiple servers is difficult because of the possibility of distributed cycles. In this figure, the three transaction's chains overlap on servers s_1 , s_2 , s_3 , but that no one server handles all three transactions. The acyclic transactions protocol prevents these transactions from forming the cycle shown on the right.

cause interactions between transactions can span multiple servers. In these cases, it is possible that no single server would have have the requisite view to detect and prevent a cycle in the graph. For example, imagine three transactions across keys k_A , k_B , and k_C , where each transaction writes to a different pair of the keys: (k_A, k_B) , (k_B, k_C) , and (k_C, k_A) . If the system only ordered the transactions pairwise, the three transactions could be committed in a non-serializable order, because no single key is written by all three transactions. Figure 3 depicts this example and highlights the problematic execution that results in a cycle between the transactions.

Servers ensure that all transactions commit in a serializable order across servers by embedding ordering information, called *mediator tokens*, into transactions. Mediator tokens are integer values that are assigned to transactions by the heads of chains. Because mediator tokens are integers, servers may determine the relative order of conflicting pair by comparing their mediator tokens. A simple invariant that ensures serializability is to commit conflicting pairs in the order specified by their mediator tokens. For example, if the mediator tokens for the conflicting pair (T_X, T_Y) have the relationship mediator (T_X) < mediator (T_Y) , then all servers order the transactions such that T_X commits before T_Y .

The acyclic transactions protocol relies on this invariant to order transactions. Upon receipt of a transaction passing forward through the chain, a server compares the transaction's mediator token to the largest mediator token across all transactions that previously read or wrote any of the current transaction's objects. If the current mediator token is larger than the previous token, the transaction

is forwarded to the next server in the chain. If, however, the mediator token is less than the previous token, a "retry" message is sent backwards in the chain to the head, where the transaction will be retried with a larger mediator token.

2.1.4 Generating Mediator Tokens

At first glance, mediator tokens may resemble timestamps that are typically used by transaction commit protocols, but mediator tokens are significantly more flexible. Systems based upon timestamps, whether they be logical timestamps [29] or synchronized wall clocks, impose restrictions on how timestamps may be generated. Namely, timestamps must be generated in a monotonic fashion so that the system never moves backward in time. Failing to preserve the monotonicity of timestamps would permit transactions to commit in an unserializable fashion. Mediator tokens impose no such restrictions on token generation.

The flexibility of mediator tokens permits a wide array of implementation strategies. For example, a simple token generation strategy would be to always set a transaction's initial token to zero, choosing successively larger values on each subsequent pass. Another strategy would be to generate tokens at random and ensure that each subsequent pass draws from a range of tokens that are strictly greater than the token of the previous pass. A strategy that limits the number of retries is for each server to maintain a counter to generate mediator tokens. Servers may generate a new mediator token by reading the counter's current value and incrementing the counter. When a server sees a mediator token that is greater than the next value to be generated by its counter, it may advance the counter to be greater than this other token. Because mediator tokens are flexible, storage servers do not need to carefully manage or preserve this counter during server failover, and do not need to synchronize counters across servers.

2.2 Fault Tolerance and Durability

In a large-scale deployment, failures are inevitable. Acyclic transactions accommodate a natural way to overcome such failures. Specifically, acyclic transactions permit a subchain of f+1 replicas to be inlined into the longer chain in place of a single data server. This allows the system to remain available despite up to f failures within a subchain. Chain replication maintains a well-ordered series of updates within each subchain. Operations that traverse the acyclic transaction chain in the forward direction pass forward through all inlined chains. Likewise, operations that traverse the chain in reverse traverse inlined chains in reverse.

The notion of fault-tolerance provided by acyclic transactions is different from the notion of durability

within traditional databases. While durability ensures that data may be re-read from disk after a failure, the system remains unavailable during the failure and recovery period; in contrast, acyclic transactions' fault tolerance mechanism ensures that the system remains available so long as the number of failures remains below the configured threshold.

2.3 Atomicity, Consistency, Isolation

The protocol guarantees atomicity, consistency, and isolation for all transactions. These properties naturally follow from the one-copy serializability upheld by the protocol. Each transaction completes in its entirety at a well-defined point in the partial order, where its effects are either completely visible to subsequent transactions, or it aborts without effect. Every server ensures that the stored objects are well-formed and match their data types. Overall, acyclic transactions guarantee that operations within a transaction execute with mutual exclusion from each other, as if there were a single giant lock protecting the database.

2.4 Correctness

By leveraging a fault tolerant system coordinator, acyclic transactions uphold both liveness and safety in the presence of up to f faults. Specifically, acyclic transactions maintain serializability at all times, and will eventually commit or abort every transaction assuming at most f of the f+1 replicas of the data remain non-faulty. In this section we demonstrate how the acyclic transactions protocol maintains these safety and liveness properties.

Safety: The acyclic transactions protocol provides serializability by ensuring that the final system state is equivalent to a serial schedule. The protocol upholds this guarantee by ensuring that the dependency graph across all transactions is acyclic. Intuitively, every conflicting pair directly corresponds to an edge in this graph, while the mediator tokens enforce the anti-cycle property.

Because non-conflicting pairs operate on disjoint sets of data, the conflicting pairs are the only transaction pairs whose order must be carefully managed. A conflicting pair of transactions is committed in the same order on all common servers in order to ensure that operations to their shared state are applied in the same order. Servers use mediator tokens to decide the commit order for transactions in a conflicting pair; every server will enforce the order specified by the transactions' tokens.

Globally, mediator tokens preserve transitive relationships across transactions, ensuring that cycles cannot arise in the dependency graph. The dependency graph is structured such that each edge is a conflicting pair (T_x, T_y) such that either mediator $(T_x) < \text{mediator}(T_y)$ or $\text{mediator}(T_x) > \text{mediator}(T_y)$. In the former case, the graph will contain an edge $T_x \leadsto T_y$, while in the latter

case, the graph will contain edge $T_y \rightsquigarrow T_x$. Any directed path will consist of edges such that the mediator token for the source is less than the mediator token for the destination. Transitively, the start of the path must have a mediator token less than the end of the path. Thus, it is impossible for the graph to contain a cycle, because a cycle would imply that there exists a directed path—and thus, a directed edge—from a transaction with a higher mediator token to a transaction with a lower mediator token. Because the system prohibits committing transactions in an order that contradicts the ordering established by their mediator tokens, it is impossible for such an edge, and thus a cycle, to exist.

Liveness: The protocol remains available for processing transactions during a bounded number of server failures. Specifically, the protocol will always be able to commit or abort a transaction so long as at most f servers fail of the f+1 servers assigned to replicate each key. To enable the system to detect and correct for these failures, acyclic transactions make use of a fault tolerant coordinator, which may be built using standard techniques [3, 8, 24]. This coordinator acts as a shepherd for the system, guiding it toward a stable state, even as servers fail or become otherwise unavailable.

The system overcomes failures by removing failed servers from the chains for actively propagating transactions. For each failure, the coordinator issues a new configuration that lists the server as failed. Non-faulty servers may consult this new configuration to determine which currently outstanding transactions contain the faulty server as the next hop in the forward direction. These transactions are retransmitted to move the transaction toward a commit or abort state. To prevent duplicate messages from affecting correctness, servers maintain a list of committed and aborted transactions. Upon receipt of a retransmitted forward-bound message, a server will first consult this list and answer with a commit or abort message if appropriate. Otherwise, the server processes the message to move the transaction closer to committing; typically this will entail sending another message forward in the chain, or waiting for a previously sent message to return "commit" or "abort". Overall, the coordinator and servers will repeat this process as necessary until transactions eventually commit or abort.

3 Implementation

We have fully implemented the system described in this paper. The code base consists of 130,000 lines of code, approximately 15,000 lines of which are devoted to processing transactions. The Warp distribution provides bindings for C, C++, Python, Ruby, Java, Go, and Node.JS and supports a rich API that goes well beyond the simple get/put interface of typical key-value stores. A system of virtual servers maps a small number of

servers to a larger number of partitions, permitting the system to reassign partitions to servers without repartitioning the data. The implementation uses a replicated state machine as the coordinator to ensure that there are no single points of failure.

3.1 Rich API

Acyclic transactions naturally support an expanded API that enables complex applications. The expanded API includes support for rich data structures, multiple independent schemas, and nested transactions.

3.1.1 Data Structures

The discussion in Section 2 presented all operations in a acyclic transaction as either a read or a write on an arbitrary string, but our implementation goes much further to support many data structures commonly used in modern applications. Warp provides programmers with integer, float, list, set, map, and document types as well as atomic operations on each of these types that enable fast concurrent operation. For example, it is possible to atomically add an element to a list, or perform arithmetic on an integer type. A write, then, may consist of any of these atomic operations and is not limited to simply overwriting the previous value. These atomic operations are especially useful for cases where acyclic transactions enable low abort and retry rates because they allow applications to further improve concurrency.

3.1.2 Independent Schemas

Acyclic transactions generalize well from operations across multiple keys to operations across multiple keys in different schemas. In our implementation, applications may create multiple schemas—which resemble tables from traditional database systems—and store different objects in each schema without any collisions in the key space. Clients construct the chain for transactions that touch multiple schemas by lexicographically ordering servers first by schema, then by key.

3.1.3 Nested Transactions

The architecture we have presented naturally supports nested transactions with only minimal changes to the client library. Nested transactions may be implemented by allowing transaction contexts to recursively refer to each other. Each nested transaction maintains its own locally-managed transaction context with a pointer to the parent transaction's context. Reads recursively query the parent context until either a cached value is read, or the root context issues the query to a storage server. Writes are stored in the transaction context to which they are issued. At commit time, the client merges a nested transaction into its parent context, by merging the read and write sets. Nested transactions abort if the values read in the child are modified in the parent or vice-versa. The

client sends a acyclic transaction to the storage servers only when the root transaction commits.

3.2 Virtual Servers

Warp uses a system of virtual servers to map multiple partitions of the mapping to a single server. Clients construct their acyclic transaction chains by constructing a chain through the virtual servers, and then mapping these virtual servers to their respective servers. A server that maps to multiple virtual servers in a chain will appear at multiple places in the chain, where it acts as each of its virtual servers independently. Within each physical server, state is partitioned by virtual server, so that each virtual server functions as if it were independent. Virtual servers enable the system to perform dynamic load balancing more efficiently.

3.3 Coordinator

A replicated state machine called the coordinator partitions the key space across all data servers, ensures balanced key distribution, and facilitates membership changes as servers leave and join the cluster. Since the coordinator is not on the data path, its implementation is not critical to the performance of acyclic transactions.

The coordinator partitions data across servers and ensures balanced key distribution by using copyset replication [11] to group servers into replica sets. Each independent schema is partitioned across the generated copysets to create an object-to-server mapping. The coordinator over-partitions the key space to enable it to remap partitions from over-burdened replica sets to under-loaded replica sets if necessary.

As servers join and leave a cluster, the coordinator regenerates copysets to respond to new members. Servers dynamically compute the previous and next servers in each acyclic transaction's chain using the mapping; when the mapping changes, servers retransmit transactions whose chain changed. Every message carries the configuration's version to enable clients and servers to detect and re-route out-of-date requests using an up-to-date configuration. The mapping is changed incrementally, ensuring that each subsequent mapping overlaps with the previous mapping, which ensures that some replicas in each inlined chain will overlap as well. Thus, servers are always able to integrate new nodes without violating the assumptions used to construct acyclic transactions' chains.

The coordinator is implemented on top of the Replicant replicated state machine system. Replicant uses chain replication [51] to sequence the input to the state machine and a quorum-based protocol to reconfigure chains on failure. The details of Replicant are beyond the scope of this paper; the function of the coordinator could also be built on configuration services such as

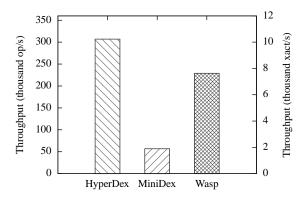


Figure 4: Total transactional throughput of the three systems. Warp outperforms MiniDex by a factor of 4, and achieves 75% the throughput of HyperDex, which Warp uses as its underlying key-value store. Warp averages approximately 7,500 transactions, or more than 225,000 individual key operations, per second in this benchmark.

Chubby [8], ZooKeeper [24], and OpenReplica [3].

4 Evaluation

In this section, we evaluate Warp's performance and scalability using both macro and micro benchmarks. The primary focus of our evaluation is on examining the performance of Warp transactions relative to other transaction processing techniques. To that end, we implemented Sinfonia's mini-transactions [2] on top of Hyper-Dex, hereafter referred to as MiniDex. Because Warp builds upon HyperDex, and because native HyperDex outperforms many NoSQL databases, we ensure a true apples-to-apples comparison by building all systems using the same code base. We also compare Warp to Hyper-Dex, even though the latter offers no transactional guarantees. The client-facing interfaces and the benchmark code is identical for all three systems.

We performed our experiments on our dedicated labsize cluster consisting of thirteen servers, each of which is equipped with two Intel Xeon 2.5 GHz E5420 processors, 16 GB of RAM, 500 GB SATA 3.0 Gbit/s hard disks, and Gigabit Ethernet. The servers are running 64-bit Ubuntu 14.04. Each storage system was configured with appropriate settings for a real deployment of this size. This includes setting the replication factor to be the minimum value necessary to tolerate one failure of any process or machine. Both the coordinators and the storage servers can each tolerate one failure. All systems provide strong consistency guarantees, which MiniDex and Warp extend across multiple objects.

4.1 TPC-C Macro Benchmark

The industry-standard TPC-C benchmark simulates an e-commerce application by specifying a mixed transac-

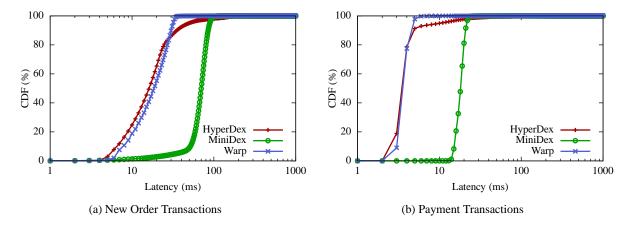


Figure 5: Write operations have similar latency in HyperDex and Warp because the cumulative lengths across all chains formed within a transaction are the same. A HyperDex transaction with O operations makes O chains of length f+1. A Warp transaction will make a single chain of length $O \times (f+1)$.

Profile	R	W	RMW	% Mix
New Order	12	3	11 (1)	45
Payment	0	1	3 (2)	45
Order Status	12	0	0	5
Stock Level	201 (1)	0	0	5

Table 1: A summary TPC-C workload. For each transaction profile, the chart shows the average number of read-only (R), write-only (W), and read-modify-write (RMW) operations. The TPC-C workload will randomly perform transactions according to this distribution. The values in parenthesis specify the numberj of district or warehouse objects per transaction.

tion workload. The workload specified by TPC-C is inherently difficult to process with optimistic concurrency control, because it includes both read-heavy and update-heavy transaction profiles and the update-heavy transactions intentionally contend on a small number of hot keys. For instance, the *new-order* transaction generates the order's identifier using a sequentially-increasing counter associated with one of one-hundred districts. The *payment* transaction increments the year-to-date totals for one of one-hundred districts and one of ten ware-houses. The contention and interaction between the new-order and payment transaction profiles is what makes the TPC-C benchmark a compelling choice for testing new optimistic protocols.

At the core of the benchmark are multiple transaction profiles which each represent a different type of application logic. Table 1 provides an overview of each transaction type. The values in parenthesis specify the number of district or warehouse objects per transaction. The bulk of the workload stems from the new-order and payment transaction profiles. These profiles simulate a customer

placing purchase orders, and subsequently paying the invoice. Our implementation of TPC-C retains as much functionality of the benchmark as is reasonable to implement on a key-value store. In total, the implementation consists of approximately 1100 lines of Python code that execute client side using the Python bindings to HyperDex, MiniDex, and Warp. We omitted the "delivery transaction" profile because the TPC-C benchmark specifies that it be performed by a background process that would be handled by a messaging queue in a real deployment. Because we chose to retain most of the TPC-C benchmark's behavior, our results are incomparable to others in the literature that simply perform new-order transactions [5, 50].

We deployed the TPC-C benchmark with its default setting that includes 10 warehouses, which are very contended keys, and 100 districts, which are somewhat contended keys. Each new-order or payment transaction includes one warehouse and one district in the set of keys that it reads, modifies, and writes. For the transactional systems, these keys will be the ones most likely to introduce transaction abort and retries. For the HyperDex workload, there cannot possibly be any conflict because the reads and writes may proceed in any order without transactional consistency. Intuitively, we expect that the performance of HyperDex provides an upper bound on throughput and a lower bound on latency for all experiments, because MiniDex and Warp add strictly more mechanism on top of the existing code. Consequently, the HyperDex upper bound allows us to objectively gauge how much overhead each system adds to the baseline.

Figure 4 shows the overall transactional throughput for HyperDex, MiniDex, and Warp. The experiment shows that that Warp achieves a throughput that is four times higher than MiniDex, and close to 7,500 transactions, or 225,000 operations, per second. To put the factor of 4 in perspective, Warp achieves 75% the throughput of the non-transactional system on which it builds, while MiniDex does not even realize 20% of its potential.

The intuition for why Warp is so much more efficient is two-fold: first, Warp's transaction management allows more concurrency than is possible with MiniDex; and second, Warp's communication costs are similar to those of the baseline and require no additional messages. Both systems construct chains to write data into the system, where each link in the chain equates to a network round trip. Where HyperDex will construct one chain of length f+1 for each of the O operations, Warp will commit the operations through a single chain of length $O \times (f+1)$ to commit the transaction. Thus, in the common case of no aborts and no retries, Warp requires no additional round trips beyond those required for a write within HyperDex. Figures 5a and 5b show latency CDFs for the new-order and payment transaction profiles. We can see that for both transaction types, the latency of HyperDex and Warp follow a similar trend, while the latency of MiniDex is approximately five times higher.

Because transactions must validate read operations, there's an additional cost to performing a transactional read that is not paid for non-transactional workloads. The read that the Warp client library performs to pull the object into the transaction context is the same cost as the read that the non-transactional code will perform. The Warp client then validates the read at commit time. In figure 6, we directly quantify the latency profile of the read-only "order status" transaction. We can see that Warp's latency is approximately three times higher than the non-transactional measurement, while the MiniDex latency is approximately six times higher.

Overall, the reason MiniDex achieves lower throughput and higher latency is because mini-transactions are more likely to abort. We observed, on average, only 5% of transactions complete without aborting or retrying at least once, and we've included the time taken to retry transactions in the above numbers for all systems. Because all three systems use the same benchmark and baseline code, the performance difference is solely the commit protocol in use. MiniDex cannot permit multiple transactions to prepare for the same key simultaneously, forcing transactions to abort or wait, which increases the latency by a small constant multiplier. Warp permits these transactions to prepare simultaneously, enabling it to complete all transactions without aborting.

Although it may seem possible to relax the minitransactions protocol to permit transactions to prepare for the same key simultaneously, doing so would break serializability. A modified MiniDex would require ad-

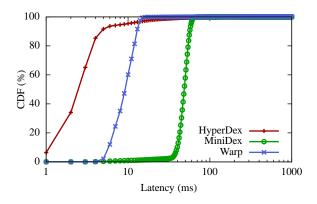


Figure 6: Read operations have different latencies inside and outside of a transaction. A non-transactional read may be directly performed against the server. A transactional read includes that latency, plus the cost of validating the read at commit time.

ditional mechanisms to prevent the potential cycle illustrated in Figure 3, as concurrently prepared transactions could commit in different orders on different servers. Even HyperDex's atomic operations cannot enable such a relaxed commit protocol because they cannot affect the order in which operations occur on different servers.

4.2 Micro-Benchmarks

In order to gain insight into the behavior of Warp's acyclic transactions, we examine the results from several targeted micro-benchmarks. In all of these micro-benchmarks, objects have 12 B keys and 64 B values, and are constructed uniformly at random. Ten million objects are preloaded onto the cluster before performing each benchmark.

4.2.1 Read/Write Ratio

In order to quantify the effects of the read/write ratio on a transactions' throughput, we constructed a microbenchmark that varies the read-write ratio for operations of constant size. This micro-benchmark constructs transactions that involve exactly eight objects, and randomly read from or write to random objects. Each operation is randomly chosen to be a read or a write so that the total percentage of write operations matches the independent variable. In HyperDex, a read incurs one round trip, while a write incurs f + 1 round trips. Thus, we expect that a write-heavy workload in HyperDex will achieve lower throughput than a read-heavy workload, with all other factors fixed. Because of the validation step, we expect Warp transactions to be largely a matter of the latency of the commit. In Figure 7 we see the average throughput for Warp is 150,000 transactions per second, regardless of the workload, while HyperDex performance increases as read percentage increases. It

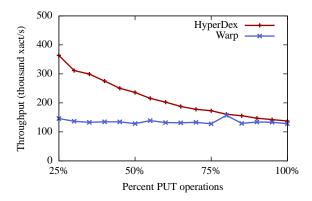


Figure 7: The ratio of read/write operations does not materially affect the throughput for transactions.

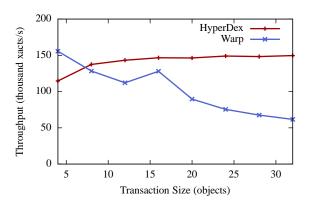


Figure 8: The total throughput of Warp is dependent on the throughput of the underlying key-value store, and of the transaction size. This graph shows the throughput of a 100% write workload as the number of keys in a transaction increases.

demonstrates that the performance is a function of the transaction protocol and not the read-write ratio.

4.2.2 Transaction Size

Naturally, the use of chains introduces a tradeoff: as transactions grow to contain more keys, the length of the resulting chains naturally increases as well. Figure 8 quantifies this tradeoff by constructing write transactions with different numbers of keys. We employ the same micro-benchmark from the previous section, and use a 100% write workload.

To test the performance impact of transaction size, we modified our previous microbenchmark to vary the number of keys in a transaction rather than the read/write ratio. In this experiment, the microbenchmark issues transactions with a configurable number of put operations on random keys. Figure 8 shows that, as expected, the number of operations per second is mostly independent of the transaction size. This demonstrates that longer trans-

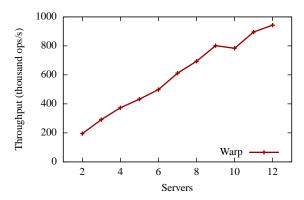


Figure 9: Warp is a scalable system. This graph shows the aggregate throughput of the system as servers are added. With each additional server, the overall throughput increases proportionally, exhibiting linear scaling.

action chains do not introduce additional overhead, and that, for this workload, the transaction rate is a linear function of the transaction size.

4.2.3 Scalability

The performance of acyclic transactions should scale linearly with the number of servers in the cluster, as the number of servers that participate in a acyclic transaction is dependent only on the transaction size. Adding more servers to the cluster should therefore yield a proportional increase in performance by spreading the work across more servers. Figure 9 shows the aggregate throughput of a two-key transaction from our microbenchmark with different cluster sizes. Not surprisingly, Warp throughput scales linearly with cluster size.

4.3 Summary

Overall, the acyclic transactions protocol provides a low overhead means of ensuring serializable transactions in a distributed key value store. Despite providing ACID guarantees, Warp achieves throughputs close to those associated with non-transactional data stores. This is primarily due to the way acyclic transactions constrict data to chains that avoid bottlenecks at dedicated transaction managers. This level of performance does not require static analysis of applications, or dependency on synchronicity assumptions, or reliance on loosening application semantics.

5 Related Work

Transaction management has been an active research topic since the early days of distributed database systems. Existing approaches can be broadly classified into the following categories based upon the mechanisms employed and resulting guarantees.

Optimistic Concurrency Control: Acyclic transactions are a form of optimistic concurrency control [26] because a validation step is necessary to prevent conflicts among concurrent transactions. Traditionally, optimistic concurrency control schemes have been divided into backward-oriented and forward-oriented schemes [49]. The former checks optimistic reads against previously performed writes, while the latter checks optimistic writes against concurrently executing, unvalidated reads. Warp's concurrency control is most similar to backward oriented OCC, but includes additional validation steps beyond those typically employed in backward oriented systems because it permits transactions to execute concurrently.

Centralized: Early RDBMS systems relied on physically centralized transaction managers [9]. While centralization greatly simplifies the implementation of a transaction manager, it poses a performance and scalability bottleneck and is a single point of failure. Warp is based on a distributed architecture.

Distributed: The traditional approach to distributing transaction management is to provide a set of specialized transaction managers that serve as intermediaries between clients and back-end data servers. These transaction managers perform lock or timestamp management [7], and employ a protocol, such as two phase-commit, for coordination. In the class of two-phase commit protocols, Linear 2PC [19] is similar to Warp in that the communication pattern is arranged along a chain of servers. The key improvement of acyclic transactions over existing multi-phase protocols, including Linear 2PC, is that it does not employ specialized transaction managers and permits multiple transactions to execute in parallel directly on a subset of storage servers, even when operating on the same key(s).

A recent proposal [34] suggests physically separating the transaction processing component from the storage component so that transaction processing remains agnostic to the structure of the storage. The resulting system, Deuteronomy [31] performs this separation so that transaction management remains isolated from scaling decisions made at the storage layer. ElasTraS [15] uses two layers of transaction management to separately process read-only and read-write transactions, where each layer and the underlying storage are independently scalable. Separating transaction management from data storage does not fundamentally make the transaction management more scalable because it does not alter the spurious coordination naturally present in the transaction manager. Warp reduces spurious coordination and centralized bottlenecks by employing a completely distributed protocol.

Recent work has proposed database systems with

minimal coordination through the use of a technique called \mathcal{I} -confluence analysis [5]. \mathcal{I} -confluence requires of the programmer a set of invariants that are processed by offline analysis to determine a minimal amount of coordination to uphold the invariants. Warp transactions are fully serializable, require no programmer-provided specifications, and naturally avoid spurious coordination.

Consensus-based: Recent work has examined how to use a general consensus protocol, such as Paxos [28] or Zab [24], to serialize transactions in a fault-tolerant manner. Although consensus seems unrelated to transaction management, the classic two-phase commit algorithm is actually a special f=0 case of Paxos that cannot tolerate coordinator failure [22].

Straightforward application of consensus protocols, however, would introduce spurious coordination by applying a total order across all transactions. Consequently, consensus-based systems typically use some combination of data partitioning [6, 21, 43, 45], Generalized Paxos [25] or transaction batching [44, 50] to increase opportunities for parallel execution.

Warp uses consensus only to maintain system metastate. The acyclic transactions protocol, inspired by chain-replication [51] and value-dependent chaining [17], relies upon consensus for system membership and coordination, but not for actual transaction processing. Because consensus is not on the critical path for any acyclic transaction, the protocol is able to completely eliminate any consensus-induced overhead.

Synchronized clocks: Some notable systems in this space take advantage of synchronized clocks to order transactions. Adya et. al. [1] support serializable transactions and use loosely synchronized clocks as a performance optimization. Spanner [13] uses tightly synchronized clocks, with bounded error, to achieve high-throughput and external consistency for transactions across multiple data centers. Granola [14] orders independent transactions with no locking overhead or abort mechanism, and orders these transactions using time synchronization as an optimization.

Warp is an asynchronous protocol that makes no assumptions about clock synchrony. It is more robust than systems which make synchronicity assumptions, and requires less maintenance and operations infrastructure. Most systems in this category remain correct should synchronicity assumptions be violated, but suffer varying degrees of performance degradation. A notable exception is Spanner, which preserves serializability only when its assumptions are upheld.

Client-managed transactions: Some systems build on existing storage by implementing transactions directly in the client library. Such systems mediate concurrent transactions by embedding additional attributes into the

stored objects to enable concurrency control. CrSO [18] uses HBase versions and a centralized status oracle to check for read-write or write-write conflicts at commit time. Percolator [38] maintains Google's search index by storing both data and locks in BigTable.

The downside to client-managed approaches is that they require mechanisms to cope with client failure. CrSO requires a background process to cleanup stale versions of objects written by failed transactions. Percolator uses a background mechanism to break locks held by failed processes. Warp incurs no such cost because failed clients leave behind no state to clean up.

Geo-Replication: For geo-replicated storage, many systems avoid synchronous WAN latencies by making guarantees weaker than serializability. COPS-GT [32] and Eiger [33] provide read and write transactions, respectively, that commit locally and propagate to remote data centers in a causally-consistent fashion. Walter [46] implements parallel snapshot isolation using counting sets to resolve conflicting versions, similar to commutative data types [30]. Warp provides a strictly stronger guarantee of general purpose serializable transactions, but lacks optimizations for geo-replication.

Offline Checking: Lynx [52] uses chains for replication and guarantees serializability, but requires a priori knowledge of transactions and static analysis to prevent non-serializable executions. The key insight in Lynx is that this static analysis can break one application-level transaction into many smaller transactions that execute piecewise across servers. Rococo [35] also requires offline analysis of transactions in order to decompose them into smaller atomic units, which it then executes in parallel. Warp is fundamentally different from transaction management schemes that rely upon offline checking because it guarantees serializability without requiring that transactions are known a priori, and without requiring any static analysis across all transactions.

Workload Partitioning: Some systems improve performance by constraining transactions to operate within single partitions of the data store. G-Store [36] provides serializable transactions on top of HBase by grouping keys' primary replicas on a single server so that transactions require no cross-server communication. H-Store [48] targets OLTP applications and efficiently supports such constrained tree applications by guaranteeing that transactions are executed by a single server. Warp imposes no constraint on transactions, enabling maximal flexibility in data placement.

Mini-Transactions: Sinfonia [2] introduces the minitransaction primitive which allows an application to specify sets of checks, reads, and writes and commit the result using a modified two-phase commit. The payload of a mini-transaction is the same as the payload

of a acyclic transaction. Indeed, the protocols can be quite similar in their behavior: both are optimistic, both require two (or more) phases to commit a transaction across multiple servers, and both have the client library optimistically execute reads and writes to be validated at commit time.

Where mini-transactions and acyclic transactions differ is in their commit behavior. Acyclic transactions allow multiple transactions that read or write the same key to simultaneously execute and commit in a serializable order. Additionally, mini-transactions are vulnerable to client failure while acyclic transactions are naturally fault tolerant. These differences cannot be overcome by simply loosening the commit requirements within Sinfonia, because the resulting mechanism not be serializable.

Key-Value Stores: Key-value systems are defined by their distributed architecture that offers performance and scalability, often obtained by avoiding strong consistency or transactional guarantees. This trade-off is often an engineering decision to mask latency, and is not fundamental. Amazon's Dynamo [16] and its derivatives [27, 39, 41] guarantee only eventual consistency in order to increase write availability by writing data to sloppy quorums. Yahoo!'s PNUTS [12] makes a slightly stronger guarantee of per-object timeline consistency, but makes no guarantees across multiple objects. Google's BigTable [10] provides linearizable access to individual rows, but does not make cross-object guarantees. BigTable's consistency is the same as HyperDex [17], the system Warp builds upon. Warp's guarantee is strictly stronger as it extends serializability across multiple ob-

More generally, these NoSQL systems have roots in Distributed Data Structures [23] and distributed hash tables [40, 42, 47, 53], which provide efficient access to individual objects, usually in the form of a key-value store. Other notable work on key-value stores includes FAWN-KV [4], a linearizable key-value store built to reduce power consumption in storage systems; Comet [20], a key-value store that stores clients' code alongside the stored objects; RAMCloud [37], which builds a keyvalue store for low-latency networks; and FaRM, which uses RDMA to build a fast in-memory key-value store with single-machine transactions. The goals of these systems are orthogonal to those in Warp, and the techniques could be combined to make a transactional key-value store with low power consumption (maximizing transactions per watt), or low latency (minimizing transaction completion time).

6 Conclusion

This paper describes Warp, a key-value store that provides one-copy-serializable ACID transactions. The main insight behind Warp is a protocol called acyclic

transactions which enables the system to completely distribute the task of ordering transactions. Consequently, transactions on separate servers will not require expensive coordination and the number of servers that process a transaction is independent of the number of servers in the system. The system achieves high performance on a variety of standard benchmarks, performing nearly as well as the non-transactional key-value store that Warp builds upon.

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