

Highly Available Transactions: Virtues and Limitations

Peter Bailis[†], Aaron Davidson[†], Alan Fekete[◊], Ali Ghodsi^{†,‡}, Joseph M. Hellerstein[†], Ion Stoica[†]
[†] UC Berkeley [◊] University of Sydney [‡] KTH/Royal Institute of Technology

ABSTRACT

To minimize network latency and remain online during server failures and network partitions, many modern distributed data storage systems eschew transactional functionality, which provides strong semantic guarantees for groups of multiple operations over multiple data items. In this work, we consider the problem of providing Highly Available Transactions (HATs): transactional guarantees that do not suffer unavailability during system partitions or incur high network latency. We introduce a new taxonomy of highly available systems and analyze existing ACID and distributed consistency guarantees to identify which can and cannot be achieved in HAT systems. This unifies the literature on weak isolation, replica consistency, and highly available systems. We analytically and experimentally quantify the availability and performance benefits of HATs—often two to three orders of magnitude over wide-area networks—as well as their necessary semantic compromises.

1 Introduction

The last decade has seen a significant shift in the design of large-scale database systems, from the use of transactional RDBMSs [12, 41, 40] to the widespread adoption of loosely consistent distributed key-value stores [20, 23, 31]. The 2000 introduction of Brewer’s CAP Theorem, which stated that a highly available system cannot provide strong consistency guarantees in the presence of network partitions, helped spur this shift [14]. As formally proven [38], the CAP Theorem concerns linearizability: the ability to read the most recent write to a data item that is replicated across servers [44]. Yet the implications of CAP—which concern a fairly narrow form of distributed consistency—have often been conflated with the ability to provide ACID database properties [10, 14, 22]; this misunderstanding has led to substantial confusion regarding replica consistency, transactional isolation, and high availability. The recent resurgence of transactional systems like Spanner [25] suggests that programmers value these semantics, but, unfortunately, existing transactional data stores do not provide availability in the presence of partitions [18, 22, 45, 25, 35, 47, 48, 53, 64, 66].

Indeed, serializable transactions—the gold standard of traditional ACID databases—are not achievable with high availability in the presence of partitions [29]. However, database systems have a long tradition of providing weaker isolation and consistency guarantees [2, 11, 40, 41, 46]. Today’s ACID and NewSQL databases often employ weak isolation models due to concurrency and performance benefits; weak isolation is overwhelmingly the default setting in these stores and is often the only option offered (Section 3). While weak isolation levels do not provide serializability for general-purpose transactions, they are apparently strong enough to deliver acceptable behavior to many application programmers and are substantially stronger than the semantics provided by current highly available systems. This raises a natural question: which of these semantics can be provided with high availability?

To date, the relationship between ACID semantics and high availability has not been well explored. We have a strong understanding

of weak isolation in the single-server context from which it originated [2, 11, 41] and many papers offer techniques for providing distributed serializability [12, 25, 27, 45, 48, 66, 71] or snapshot isolation [28, 35, 50, 64]. Additionally, the distributed computing and parallel hardware literature contains many consistency models for single operations on replicated objects [23, 44, 53, 54, 65]. However, the literature lends few clues for providing semantic guarantees for multiple operations operating on multiple data items in a highly available distributed environment.

Our main contributions in this paper are as follows. We fill the gap between the many previously proposed isolation and consistency models and the goal of high availability. We classify which among the wide array of models are achievable with high availability, denoting them as *Highly Available Transactions* (HATs). In doing so, we demonstrate that although many implementations of HAT semantics are not highly available, this is an artifact of the implementations rather than an inherent property of the semantics. Our investigation shows that, besides serializability, Snapshot Isolation and Repeatable Read isolation are not HAT-compliant, while most other isolation levels are achievable with high availability. We also demonstrate that many weak replica consistency models from distributed systems are both HAT-compliant and simultaneously achievable with several ACID properties.

Our investigation is based on both impossibility results and several constructive, proof-of-concept algorithms. For example, Snapshot Isolation and Repeatable Read isolation are not HAT-compliant because they require detecting conflicts between concurrent updates (as needed for preventing Lost Updates or Write Skew phenomena), which we show is unavailable. However, Read Committed isolation, Transactional Atomicity, and many of the weaker data consistency models from database and distributed systems are achievable via algorithms that rely on multi-versioning and limited client-side caching. For several guarantees, such as causal consistency with phantom prevention and ANSI Repeatable Read, we consider a modified form of high availability in which clients “stick to” (i.e., have affinity with) at least one server—a property which is often implicit in the distributed systems literature [44, 53, 54] but which requires explicit consideration in a client-server replicated database context. This sticky availability is widely employed [53, 70] but is less restrictive (and therefore more easily achievable) than traditional high availability.

Our results demonstrate that a wide range of semantic guarantees can be delivered with availability in face of partitions, but which guarantees are worthwhile in practice? We study the virtues and limitations of both classic and HAT systems by surveying practitioner accounts and research literature, performing experimental analysis on modern cloud infrastructure, and analyzing representative applications for their semantic requirements. Our experiences with a HAT prototype running across multiple geo-replicated datacenters indicate that HATs offer a one to three order of magnitude latency decrease compared to traditional distributed serializability protocols, and they can provide acceptable semantics for a wide range of programs, especially those with monotonic logic and com-

mutative updates [4, 63]. HAT systems can also enforce arbitrary foreign key constraints for multi-item updates and, in some cases, provide limited uniqueness guarantees. However, particularly for programs with non-monotonic logic, HATs can fall short, requiring sometimes-unavailable mechanisms that are more coordination intensive. Overall, this paper quantifies the benefits that Highly Available Transactions offer as well as the necessary restrictions that they place on applications.

2 Why High Availability?

Why does high availability matter? Peter Deutsch starts his classic list of “Fallacies of Distributed Computing” with two concerns fundamental to distributed database systems: “1.) The network is reliable. 2.) Latency is zero” [33]; in a distributed setting, network failures may prevent database servers from communicating, and, in the absence of failures, communication is slowed by factors like physical distance and, more often, congestion and routing. As we will see (Section 4), highly available system design mitigates the effects of network *partitions* and *latency*. In this section, we draw on a range of evidence that indicates that partitions occur relatively frequently in real-world deployments and best-case latencies between datacenters are substantial, often on the order of several hundreds of milliseconds.

2.1 Network Partitions at Scale

According to James Hamilton, Vice President and Distinguished Engineer on the Amazon Web Services team, “network partitions should be rare but net gear continues to cause more issues than it should” [42]. Anecdotal evidence confirms Hamilton’s assertion. In April 2011, a network misconfiguration led to a twelve-hour series of outages across the Amazon EC2 and RDS services [6]. Subsequent misconfigurations and partial failures such as another EC2 outage in October 2012 have led to full site disruptions for popular web services like Reddit, Foursquare, and Heroku [34]. At global scale, hardware failures—like the 2011 outages in Internet backbones in North America and Europe due a router bug [62]—and misconfigurations like the BGP faults in 2008 [56] and 2010 [57] can cause widespread partitions.

Many of our discussions with practitioners—especially those operating on public cloud infrastructure—as well as reports from large-scale operators like Google [30] confirm that partition management is an important consideration for service operators today. System designs that do not account for partition behavior may prove difficult to operate at scale: for example, less than one year after its announcement, Yahoo!’s PNUITS developers explicitly added support for weaker, highly available operation. The engineers explained that “strict adherence [to strong consistency] leads to difficult situations under network partitioning or server failures...in many circumstances, applications need a relaxed approach” [58].

Several recent studies rigorously quantify partition behavior. A 2011 study of several Microsoft datacenters found a mean of 40.8 network link failures per day (95th percentile: 136), with a median time to repair of around five minutes (and up to one week). Perhaps surprisingly, provisioning redundant networks only reduces impact of failures by up to 40%, meaning network providers cannot easily curtail partition behavior [39]. A 2010 study of over 200 wide-area routers found an average of 16.2–302.0 failures per link per year with an average annual downtime of 24–497 minutes per link per year (95th percentile at least 34 hours) [69]. In HP’s managed enterprise networks, WAN, LAN, and connectivity problems account for 28.1% of all customer support tickets while 39% of tickets relate to network hardware. The median incident duration for highest priority tickets ranges from 114–188 minutes and up to a full day for

	C	D
B	1.08	3.12
C		3.57

(a) Across us-east AZs

	H2	H3
H1	0.55	0.56
H2		0.50

(b) Within us-east-b AZ

	OR	VA	TO	IR	SY	SP	SI
CA	22.5	84.5	143.7	169.8	179.1	185.9	186.9
OR		82.9	135.1	170.6	200.6	207.8	234.4
VA			202.4	107.9	265.6	163.4	253.5
TO				278.3	144.2	301.4	90.6
IR					346.2	239.8	234.1
SY						333.6	243.1
SP							362.8

(c) Cross-region (CA: California, OR: Oregon, VA: Virginia, TO: Tokyo, IR: Ireland, SY: Sydney, SP: São Paulo, SI: Singapore)

Table 1: Mean RTT times on EC2 (min and max highlighted)

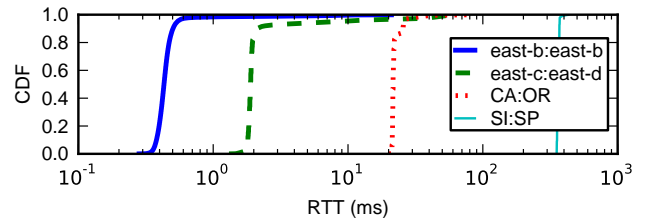


Figure 1: CDF of round-trip times for slowest inter- and intra-availability zone links compared to cross-region links.

all tickets [68]. Other studies confirm these results, showing median time between failures over a WAN network of approximately 3000 seconds with a median time to repair between 2 and 1000 seconds [55] as well as frequent path routing failures on the Internet [49]. Isolating, quantifying, and accounting for these network failures is an area of active research in networking community [51].

These results—which do not consider server failures—indicate that network partitions *do* occur within and across modern datacenters. We observe that, as a general trend, partitions exist and must accordingly be met with either unavailability at some servers or, as we will discuss, relaxed semantic guarantees.

2.2 Latency and Planet Earth

Even with fault-free networks, distributed systems face the challenge of network communication latency, Deutsch’s second “Fallacy.” In this section, we quantify round-trip latencies, which are often large—hundreds of milliseconds in a geo-replicated, multi-datacenter context. Fundamentally, the speed at which two servers can communicate is (according to modern physics) bounded by the speed of light. In the best case, two servers on opposite sides of the Earth—communicating via a hypothetical link along the planet’s diameter—require a minimum 85.1ms RTT (133.7ms if sent at surface level). As services are replicated to multiple, geographically distinct sites, this cost of communication increases.

In real deployments, messages travel slower than the speed of light due to routing, congestion, and server-side overheads. To illustrate the difference between intra-datacenter, inter-datacenter, and inter-planetary networks, we performed a measurement study of network behavior on Amazon’s EC2, a widely used public compute cloud. We measured one week of ping times (i.e., round-trip times, or RTTs) between all seven EC2 geographic “regions,” across three “availability zones” (closely co-located datacenters), and within a single “availability zone” (datacenter), at a granularity

of 1s (dataset to be released). We summarize the results of our network measurement study in Table 1. On average, intra-datacenter communication (Table 1a) is between 1.82 and 6.38 times faster than across geographically co-located datacenters (Table 1b) and between 40 and 647 times faster than across geographically distributed datacenters (Table 1c). The cost of wide-area communication exceeds the speed of light: for example, while a speed-of-light RTT from São Paulo to Singapore RTT is 106.7ms, ping packets incur an average 362.8ms RTT (95th percentile: 649ms). As shown in Figure 1, the distribution of latencies varies between links, but the trend is clear: remote communication has a substantial cost.

3 ACID in the Wild

The previous section demonstrated that distributed systems must address partitions and latency: what does this mean for distributed databases? Database researchers and designers have long realized that serializability is not achievable in a highly available system [29], meaning that, in environments like those in Section 2, database designs face a choice between availability and strong semantics. However, even in a single-node database, the coordination penalties associated with serializability can be severe, manifesting themselves in the form of decreased concurrency (and, subsequently, performance degradation, scalability limitations, and, often, external aborts like deadlocks) [41]. Accordingly, to increase concurrency, database systems offer a range of ACID properties weaker than serializability: the host of so-called *weak isolation* models describe varying restrictions on the space of schedules that are allowable by the system [2, 5, 11]. None of these weak isolation models guarantees serializability, but, as we see below, their benefits are often considered to outweigh costs of possible consistency anomalies that might arise from their use.

To understand the prevalence of weak isolation, we recently surveyed the default and maximum isolation guarantees provided by 18 databases, often claiming to provide “ACID” or “NewSQL” functionality [8]. As shown in Table 2, only three out of 18 databases provided serializability by default, and eight did not provide serializability as an option at all. This is particularly surprising when we consider the widespread deployment of many of these non-serializable databases, like Oracle 11g, which are known to power major businesses and product functionality. Given that these transactional models are frequently used, our inability to provide serializability in arbitrary HATs appears non-fatal for practical applications. If application writers and database vendors have already decided that the benefits of weak isolation outweigh potential application inconsistencies, then, in a highly available environment that prohibits serializability, similar decisions may be tenable.

It is unknown *which* of these guarantees can be provided with high availability, or are HAT-compliant. Existing algorithms for providing weak isolation are often designed for a single-node context and are, to the best of our knowledge, unavailable due to reliance on concurrency control mechanisms like locking that are not resilient to partial failure (Section 6.1). Moreover, we are not aware of any prior literature that provides guidance as to the relationship between weak isolation and high availability: prior work has examined the relationship between serializability and high availability [29] and weak isolation in general [2, 11, 41] but not weak isolation and high availability together. A primary goal in the remainder of this paper is to understand which models are HAT-compliant.

4 High Availability

To understand which guarantees can be provided with high availability, we must first define what high availability means. In this

Database	Default	Maximum
Actian Ingres 10.0/10S	S	S
Aerospike	RC	RC
Akiban Persistit	SI	SI
Clustrix CLX 4100	RR	RR
Greenplum 4.1	RC	S
IBM DB2 10 for z/OS	CS	S
IBM Informix 11.50	Depends	S
MySQL 5.6	RR	S
MemSQL 1b	RC	RC
MS SQL Server 2012	RC	S
NuoDB	CR	CR
Oracle 11g	RC	SI
Oracle Berkeley DB	S	S
Oracle Berkeley DB JE	RR	S
Postgres 9.2.2	RC	S
SAP HANA	RC	SI
ScaleDB 1.02	RC	RC
VoltDB	S	S

RC: read committed, RR: repeatable read, SI: snapshot isolation, S: serializability, CS: cursor stability, CR: consistent read

Table 2: Default and maximum isolation levels for ACID and NewSQL databases as of January 2013 (from [8]).

section, we will formulate a model that captures a range of availability models, including high availability, availability with stickiness, and transactional availability.

Informally, highly available algorithms ensure “always on” operation and guaranteed low latency. If users of a highly available system are able to contact a (set of) server(s) in a system, they are guaranteed a response; this means servers will not need to communicate with any others. If servers are partitioned from one another, they do not need to stall in order to provide clients a “safe” response to operations. This lack of fast-path coordination also means that a highly available system also provides low latency [1]; in a wide-area setting, clients of a highly available system need not wait for cross-datacenter communication. To properly describe whether a *transactional* system is highly available, we need to describe what servers a client must contact as well as what kinds of responses a server can provide, especially given the possibility of aborts.

4.1 Replica Availability

Traditionally, a system provides *high availability* if every user that can contact a correct (non-failing) server eventually receives a response from that server, even in the presence of arbitrary, indefinitely long network partitions between servers [38].¹ As in a standard distributed database, designated servers might perform operations for different data items; a server that can handle an operation for a given data item is called a *replica* for that item.²

In addition to high availability, which allows operations on any replica, distributed algorithms often assume a model in which clients always contact the same (sets of) replica(s) across subsequent operations. As we will discuss in Section 5, clients can ensure continuity between operations (e.g., reading their prior updates to a data item) by maintaining affinity or “stickiness” with a server or set of servers [70]. Simultaneously maintaining availability and stickiness requires fate sharing between the client and its server: if

¹Under this definition, systems that require a majority of servers to be online is not available. Similarly, a system which ensures that clients receive a response with high (but not perfect) probability is not available.

²There is a further distinction between a *fully replicated* system, in which all servers are replicas for all data items, and a *partially replicated* system, in which at least one server acts as a replica for only a subset of all data items. For generality, and, for applicability to many modern “sharded” or “partitioned” data storage systems [20, 23, 25, 31, 45], we consider partially replicated systems.

a client’s sticky servers fail or if the client is partitioned from its sticky servers, then it may face unavailability. We say that a system provides *sticky availability* if, whenever a client’s operation is executed against a correct server that has observed all of its prior operations, it eventually receives a response, even in the presence of indefinitely long partitions. A client may choose to become sticky available by acting as a server itself; for example, a client might cache its reads and writes [9, 65, 73]. Any guarantee achievable in a highly available system is achievable in a sticky high availability system but not vice-versa.

4.2 Transactional Availability

Until now, we have considered single-object, single-operation availability. This is standard in the distributed systems literature (e.g., distributed register models such as linearizability all concern single objects [44]), yet the database literature largely focuses on transactions: groups of multiple operations over multiple objects. Accordingly, by itself, replica availability is insufficient to describe availability guarantees for transactions. Additionally, given the choice of *commit* and *abort* responses—which signal transaction success or failure to a client—we must take care in defining transactional availability.

If a client wishes to execute a transaction that performs operations on multiple data items, then the client must be able to contact and receive a response from at least one replica for each data item. This may result in “lower availability” than a non-transactional requirement. Additionally, given the possibility of system-initiated aborts, we need to ensure useful forward progress: a system can trivially guarantee clients a response by always aborting all transactions. However, this is an unsatisfactory system because nothing good (transaction commit) ever happens; we should require a *liveness* property [59]. We cannot guarantee that every transaction will commit—transactions may choose to abort themselves—but we need to make sure that the system will not indefinitely abort transactions on its own volition. We call a transaction abort due to a transaction’s own choosing (e.g., as an operation of the transaction itself or due to a would-be declared integrity constraint violation) an *internal abort* and an abort due to system implementation or operation an *external abort*.

We say that a system provides *transactional availability* if, given replica availability for every data item in a transaction, the transaction eventually commits (possibly after multiple client retries) or internally aborts [8]. For example, a system will violate transactional availability if a client that can contact two servers for each of the data items in its transaction does not eventually commit in the absence of internal aborts.

5 Highly Available Transactions

HAT systems provide transactions with transactional availability and either high availability or sticky high availability. They offer latency and availability benefits over traditional distributed databases, yet they cannot achieve all possible semantics. In this section, we delineate ACID, distributed replica consistency, and session consistency levels which can be achieved with high availability (transactional atomicity, variants of Repeatable Read and traditionally weaker isolation, and many session guarantees), those with sticky high availability (read your writes, PRAM and causal consistency), and properties that cannot be provided in a HAT system (those preventing Lost Update and Write Skew or guaranteeing recency). We present a full summary of these results in Section 5.3.

As Brewer states, “systems and database communities are separate but overlapping (with distinct vocabulary)” [14]. With this challenge in mind, we build on existing properties and definitions

from the database and distributed systems literature, providing a brief, informal explanation and example for each guarantee. The database isolation guarantees require particular care, since different DBMSs often use the same terminology for different mechanisms and may provide additional guarantees in addition to our implementation-agnostic definitions. We draw largely on Atul Adya’s dissertation [2] and somewhat on its predecessor work: the ANSI SQL specification [5] and Berenson et al.’s subsequent critique [11].

For brevity, we provide an informal presentation of each guarantee here (accompanied by appropriate references) but give a full set of formal definitions in our extended Technical Report [7]. In our examples, we exclusively consider read and write operations, denoting a write of value v to data item d as $w_d(v)$ and a read from data item d returning v as $r_d(v)$. We assume that all data items have the null value, \perp , at database initialization, and, unless otherwise specified, all transactions in the examples commit.

5.1 Achievable HAT Semantics

To begin, we present well-known semantics that can be achieved in HAT systems. In this section, our primary goal is feasibility, not performance. As a result, we offer proof-of-concept highly available algorithms that are not necessarily optimal or even efficient: the challenge is to prove the existence of algorithms that provide high availability. However, we briefly study a subset of their performance implications in Section 6.

5.1.1 ACID Isolation Guarantees

To begin, **Read Uncommitted** isolation is captured by Adya as *PL-1*. In this model, writes to each object are totally ordered, corresponding to the order in which they are installed in the database. In a distributed database, different replicas may receive writes to their local copies of data at different times but should handle concurrent updates (i.e., overwrites) in accordance with the total order for each item. *PL-1* requires that writes to different objects be ordered consistently across transactions, prohibiting Adya’s phenomenon *G0* (also called “Dirty Writes” [11]). If we build a graph of transactions with edges from one transaction to another if the former overwrites the latter’s write to the same object, then, under Read Uncommitted, the graph should not contain cycles [2]. Consider the following example:

$$\begin{aligned} T_1 &: w_x(1) \ w_y(1) \\ T_2 &: w_x(2) \ w_y(2) \end{aligned}$$

In this example, under Read Uncommitted, it is impossible for the database to order T_1 ’s $w_x(1)$ before T_2 ’s $w_x(2)$ but order T_2 ’s $w_y(2)$ before T_1 ’s $w_y(1)$. Read Uncommitted is easily achieved via timestamping each update in a transaction with the same timestamp (unique across transactions; e.g., combining a client’s ID with a sequence number) and applying a “last writer wins” conflict reconciliation policy at each replica. Later properties will strengthen Read Uncommitted.

Read Committed isolation is particularly important in practice as it is the default of many DBMSs (as in Section 3). Centralized implementations differ, with some based on long-duration exclusive locks and short-duration read locks [41] and others based on multiple versions. These implementations often provide recency and monotonicity properties beyond what is implied by the name “Read Committed” and what is captured by the implementation-agnostic definition: under Read Committed, transactions should not access uncommitted or intermediate versions of data items. This prohibits both “Dirty Writes”, as above, and also “Dirty Reads” phenomena. This isolation is Adya’s *PL-2* and is formalized by prohibiting Adya’s *GI*{*a-c*} (or ANSI’s *P1*, or “broad” *P1* [2.2]

from Berenson et al.). For instance, in the example below, T_3 should never see $a = 1$, and, if T_2 aborts, T_3 should not read $a = 3$:

$$\begin{aligned} T_1 &: w_x(1) \ w_x(2) \\ T_2 &: w_x(3) \\ T_3 &: r_x(a) \end{aligned}$$

It is fairly easy for a HAT system to prevent “Dirty Reads”: if each client never writes uncommitted data to shared copies of data, then transactions will never read each others’ dirty data. As a simple solution, clients can buffer their writes until they commit, or, alternatively, can send them to servers, who will not deliver their value to other readers until notified that the writes have been committed. Unlike a lock-based implementation, this implementation does not provide recency or monotonicity guarantees but it satisfies the implementation-agnostic definition.

Several different properties have been labeled **Repeatable Read** isolation. As we will show in Section 5.2.1, some of these are not achievable in a HAT system. However, the ANSI standardized implementation-agnostic definition [5] is achievable and directly captures the spirit of the term: if a transaction reads the same data twice, it sees the same value each time (preventing “Fuzzy Read,” or $P2$). In this paper, to disambiguate between other definitions of “Repeatable Read,” we will call this property “cut isolation,” since each transaction reads from a non-changing cut, or snapshot, over the data items. If this property holds over reads from discrete data items, we call it **Item Cut Isolation**, and, if we also expect a cut over predicate-based reads (e.g., `SELECT WHERE`; preventing Phantoms [41], or Berenson et al.’s $P3/A3$), we have the stronger property of **Predicate Cut Isolation**. In the example below, under both levels of cut isolation, T_3 must read $a = 1$:

$$\begin{aligned} T_1 &: w_x(1) \\ T_2 &: w_x(2) \\ T_3 &: r_x(1) \ r_x(a) \end{aligned}$$

It is possible to satisfy Item Cut Isolation with high availability by having transactions cache their reads at the client such that the values that they read for each item never changes unless they overwrite it themselves. The cache can be cleared at the end of each transaction and can alternatively be accomplished on (sticky) replicas via multi-versioning. Predicate Cut Isolation is also achievable in HAT systems via similar caching or multi-versioning that track entire logical ranges of predicates in addition to item-based reads.

5.1.2 ACID Atomicity Guarantees

Transactional atomicity (TA) is core to ACID guarantees. Although, at least by the ACID acronym, it is not an “isolation” property, TA restricts transactions’ ability to view the effects of partially completed transactions. Under TA, once some of the effects of a transaction T_i are observed by another transaction T_j , thereafter, all effects of T_i are observed by T_j . Together with item cut isolation, TA prevents Read Skew anomalies (Berenson et al.’s A5A). In the example below, under TA, because T_2 has read T_1 ’s write to y , T_2 must observe $b = c = 1$ (or later versions for each key):

$$\begin{aligned} T_1 &: w_x(1) \ w_y(1) \ w_z(1) \\ T_2 &: r_x(a) \ r_y(1) \ r_x(b) \ r_z(c) \end{aligned}$$

T_2 can also observe $a = \perp$, $a = 1$, or a later version of x . Notably, TA requires disallows reading intermediate writes (Adya’s $G1b$): observing all effects of a transaction implicitly requires observing the final (committed) effects of the transaction as well.

Perplexingly, discussions of TA are absent from existing treatments of weak isolation. This is perhaps again due to the single-node context in which prior work was developed: on a single server (or a fully replicated database), TA is achievable via lightweight locking and/or local concurrency control over data items [26]. In contrast, in a distributed environment, TA over arbitrary groups of non-located items is considerably more difficult to achieve with high availability: servers need to ensure that, regardless of replica selection, all of a client’s accesses will read a sufficiently up-to-date/“consistent” set of data items. However, replicas do not need to agree on when to choose to reveal sets of values to clients, which would require consensus. Instead, as we see below, TA only requires the equivalent of reliable broadcast (with some additional client metadata) and is achievable in HAT systems.

We sketch a highly available TA algorithm and provide greater detail our extended technical report [7]. We begin with our Read Committed algorithm, but replicas wait to reveal new writes to readers until all of the replicas for the final writes in the transaction have received their respective writes (are *pending stable*). Accordingly, replicas reveal writes asynchronously; different replicas may detect pending stability at different times. To prevent clients from reading incomplete portions of a transaction’s writes as they are being revealed (e.g., a client reads a data item that from a replica that has detected pending stability, then attempts to read another item from another replica that has not yet detected pending stability), clients include additional metadata with each write: a single timestamp for all writes in the transaction (e.g., as in Read Uncommitted) and a list of items written to in the transaction. When a client reads a write, the write’s timestamp and list of items form a lower bound on the versions that the client should read for the other items. When a client reads any data item, it attaches a timestamp to its request representing the current lower bound for that item. Replicas use this timestamp to respond with either a write matching the timestamp or a pending stable write with a higher timestamp. Clients may discard any metadata upon transaction commit, and servers keep two sets of writes for each data item: the write with the highest timestamp that is pending stable and a set of writes that are not yet pending stable.

This implementation is entirely master-less and operations never block due to replica coordination. Moreover, there are several possible optimizations that, for brevity, we do not describe here. However, one key property is that we do not dictate when writes become visible; accordingly, the algorithm is highly available. We can optimize write visibility via sticky availability by sticking clients are with disjoint groups of servers: once all of a transaction’s writes are pending stable within a group of servers, writes can be made visible (as opposed to once they are pending stable with respect to all servers). For example, in a multi-datacenter setting, all clients and servers within a datacenter may form a sticky group.

5.1.3 Session Guarantees

As is typical in the database literature (with few exceptions [27]), our models have not yet considered real-time or client-centric ordering *across* transactions. In the distributed systems literature [65, 70], many useful *safety* guarantees span multiple, non-transactional operations. In particular, *session guarantees* are used to describe guarantees across transactions within a given *session*, “an abstraction for the sequence of...operations performed during the execution of an application” [65]. Informally a session describes a context that should persist between transactions: for example, on a social networking site, all of a user’s transactions submitted between “log in” and “log out” operations might form a session.

Several session guarantees can be made with high availability:

Monotonic reads requires that, within a session, subsequent reads to a given object “never return any previous values”; reads from each item progress according to a total order (e.g., the order from Read Uncommitted).

Monotonic writes requires that each session’s writes become visible in the order they were submitted by the client. Any order on transactions should also be consistent with any precedence that a global observer would see.

Writes Follow Reads requires that, if a session observes an effect of transaction T_1 and subsequently commits transaction T_2 , then another session can only observe effects of T_2 if it can also observe T_1 ’s effects (or later values that supersede T_1 ’s). Any order on transactions should respect the reads-from order.

The above guarantees can be achieved by forcing servers to wait to reveal new writes until each write’s respective dependencies are visible on all replicas. This mechanism effectively ensures that all clients read from a globally agreed upon lower bound on the versions written. This is highly available as a client will never block due to inability to find a server with a sufficiently up-to-date version of a data item. However, it does not imply that transactions will read their own writes or, in the presence of partitions, make forward progress through the version history. The problem is that under non-sticky high availability, a system must handle the possibility that, under a partition, an unfortunate client will be forced to issue its next requests against a partitioned, out-of-date server.

The solution to this conundrum is to give up high availability and settle for sticky availability. Sticky availability permits three additional guarantees, which we first define and then prove are unachievable in a generic highly available system:

Read your writes requires that whenever a client reads a given data item after updating it, the read returns the updated value (or a value that overwrote the previously written value).

PRAM (Pipelined Random Access Memory) provides the illusion of serializing each of the operations (both reads and writes) within each session and is the combination of monotonic reads, monotonic writes, and read your writes [44].

Causal consistency [3] is the combination of all of the session guarantees [15] (alternatively, PRAM with writes-follow-reads) and is also referred to by Adya as *PL-2L* isolation [2]).

Read your writes is not achievable in a highly available system. Consider a client that executes the following two transactions:

$$\begin{aligned} T_1 &: w_x(1) \\ T_2 &: r_x(a) \end{aligned}$$

If the client executes T_1 against a server that is partitioned from the rest of the other servers, then, for transactional availability, the server must allow T_1 to commit. If the same client subsequently executes T_2 against the same (partitioned) server in the same session, then it will be able to read its writes. However, if the network topology changes and the client can only contact a different server that is partitioned from the server that executed T_1 , then the system will have to either stall indefinitely to allow the client to read her writes (violating transactional availability) or will have to sacrifice read your writes guarantees. However, if the client remains sticky with the server that executed T_1 , then we can disallow this scenario. Accordingly, read your writes, and, by proxy, causal consistency and PRAM require stickiness. Read your writes is provided by default in a sticky system. Causality and PRAM guarantees can be accomplished with well-known variants [3, 9, 52, 65, 73] of the prior session guarantee algorithms we presented earlier.

5.1.4 Additional HAT Guarantees

In this section, we briefly discuss two additional kinds of guarantees that are achievable in HAT systems.

Consistency A HAT system can make limited application-level consistency guarantees. It can often execute commutative and logically monotonic [4] operations without the risk of invalidating application-level integrity constraints and can maintain limited criteria like foreign key constraints (via TA). We do not attempt to describe the entire space of application-level consistency properties that are achievable (see Section 7) but we specifically evaluate TPC-C transaction semantics with HAT guarantees in Section 6.

Convergence To require that the system propagates writes between replicas, we can require convergence, or *eventual consistency*: in the absence of new mutations to a data item, in the absence of partitions, all servers should eventually agree on the value for each item [54, 70]. This is typically accomplished by any number of anti-entropy protocols, which periodically update neighboring servers with the latest value for each data item [32]. Establishing a final convergent value is related to determining a total order on transaction updates to each item, as in Read Uncommitted.

5.2 Unachievable HAT Semantics

While there are infinitely many HAT models (Section 7), at this point, we have largely exhausted the range of achievable, previously defined (and useful) semantics that are available to HAT systems. Before summarizing our possibility results, we will present impossibility results for HATs, also defined in terms of previously identified isolation and consistency anomalies. Most notably, it is impossible to prevent Lost Update or Write Skew in a HAT system.

5.2.1 Unachievable ACID Isolation

In this section, we demonstrate that preventing Lost Update and Write Skew—and therefore providing Snapshot Isolation, Repeatable Read, and one-copy serializability—inherently requires foregoing high availability guarantees.

Berenson et al. define *Lost Update* as when one transaction T_1 reads a given data item, a second transaction T_2 updates the same data item, then T_1 modifies the data item based on its original read of the data item, “missing” or “losing” T_2 ’s newer update. Consider a database containing only the following transactions:

$$\begin{aligned} T_1 &: r_x(a) \ w_x(a + 2) \\ T_2 &: w_x(2) \end{aligned}$$

If T_1 reads $a = 1$ but T_2 ’s write to x precedes T_1 ’s write operation, then the database will end up with $a = 3$, a state that could not have resulted in a serial execution due to T_2 ’s “Lost Update.”

It is impossible to prevent Lost Update in a highly available environment. Consider two clients who submit the following T_1 and T_2 on opposite sides of a network partition:

$$\begin{aligned} T_1 &: r_x(100) \ w_x(100 + 20 = 120) \\ T_2 &: r_x(100) \ w_x(100 + 30 = 130) \end{aligned}$$

Regardless of whether $x = 120$ or $x = 130$ is chosen by a replica, the database state could not have arisen from a serial execution of T_1 and T_2 .³ To prevent this, either T_1 or T_2 should not have committed. Each client’s respective server might try to detect that another write occurred, but this requires knowing the version of the latest write to x . In our example, this reduces to a requirement for

³In this example, we assume that, as is standard in modern databases, replicas accept values as they are written (i.e., register semantics). This particular example could be made serializable via the use of commutative updates (Section 6) but the problem persists in the general case.

Composition cost may also vary by combination. For instance, Charron-Bost proved that, to capture causality between N communicating processes, standard vector-based approaches face an upper bound of $O(N)$ storage per write [21]. This means that, with $100K$ clients, each write might be accompanied by $100K$ timestamps per vector. This is difficult to scale. By compromising on availability (e.g., treating a datacenter as a linearizable cluster), this overhead can be reduced [53], but it is much cheaper to provide, say, read your writes guarantees, than causal consistency.

Linearizability and Transactional Atomicity The relationship between linearizability and transactional atomicity is non-obvious. TA dictates that writes to multiple keys across multiple servers are made visible to readers all at once, while linearizability dictates that writes to a single key on multiple servers are made visible to all readers at once—what is different? First, in linearizable (and safe and regular) systems, writes are made visible to clients *immediately* after they finish. With transactional atomicity, there is no recency guarantee. Second, in linearizable systems, all clients see all writes at the same time. With TA as defined here, clients may see writes at different times depending on which replicas they contact. We are not aware of an analogous model in the distributed systems literature. Accordingly, despite apparent similarities, TA is incomparable with and less coordination intensive (by availability measures) than linearizability.

Visibility and Stickiness Sticky availability can improve write *visibility*: clients will be able to safely read writes more quickly in a sticky available system. In the model we discussed, it is possible to achieve several properties like monotonic reads in a highly available system by waiting to reveal a write until all servers have seen it and its relevant dependencies. However, this incurs severe visibility penalties—new writes will not become visible to clients in the presence of partitions. A client that does not want to guarantee read-your-writes (due to the sticky availability requirement) may still wish to read other clients’ writes with timeliness.

6 HAT Implications

With an understanding of which guarantees are HAT-compliant, in this section, we analyze the implications of these results for existing systems and briefly study HAT systems on public cloud infrastructure. Specifically:

1. We revisit traditional database concurrency control with a focus on coordination costs and on high availability.
2. We examine the properties required by an OLTP application based on the TPC-C benchmark.
3. We perform a brief experimental evaluation of HAT versus non-HAT properties on public cloud infrastructure.

6.1 Existing Algorithms

Most existing database transaction and concurrency control algorithms are not designed for high availability and often presume a single-server deployment or a requirement for serializability. In this section, we briefly discuss design decisions and algorithmic details that preclude high availability.

Serializability To establish a serial order on transactions, algorithms for achieving serializability of general-purpose read-write transactions in a distributed setting [12, 29, 72] require at least one RTT before committing. As an example, traditional two-phase locking for a transaction of length T may require T lock operations and will require at least one lock and one unlock operation. In a distributed environment, each of these lock operations requires coordination, either with other database servers or with a lock service.

If this coordination mechanism is unavailable, transactions cannot safely commit. Similarly, optimistic concurrency control requires coordinating via a validation step, while deterministic transaction scheduling [61] requires a scheduler. Serializability under multi-version concurrency control requires checking for update conflicts. All told, the reliance on a globally agreed total order necessitates a minimum of one round-trip to a designated master or coordination service for each of these classic algorithms. The cost of round trips will be determined by the deployment environment, as we saw in Section 2; we will demonstrate this cost on public cloud infrastructure in Section 6.3.

Non-serializability Most existing distributed implementations of weak isolation are not highly available. Lock-based proposals such as those used to provide weak isolation in Gray’s original proposal [41] do not degrade gracefully in the presence of partial failures. (Note, however, that lock-based protocols *do* offer the benefit of recency guarantees.) While multi-versioned storage systems allow for a variety of transactional guarantees, few offer traditional weak isolation (e.g., non-“tentative update” schemes) in this context. The MDCC [47] protocol offers Read Committed isolation with Lost Update avoidance but is similarly unavailable due to its reliance on preventing write conflicts. Chan and Gray’s read-only transactions have item-cut isolation with causal consistency and TA (session *PL-2L* [2]) but are unavailable in the presence of coordinator failure and assume serializable update transactions [19]; this is similar to read-only and write-only transactions more recently proposed by Eiger [53]. Causal Serializability offers a similar model (with unavailable implementation): causal consistency with a variant of Read Uncommitted between transactions that write to the same data item [60]. Brantner’s S3 database [13] and Bayou [65] can all provide variants of session *PL-2L* with high availability, but none provide this HAT functionality without substantial modification. Swift [73] and bolt-on causal consistency [9] are closest to providing maximum sticky HAT semantics. As we have seen, it is possible to implement many guarantees weaker than serializability—including guarantees that are achievable with high availability—and still not achieve high availability.

6.2 Application Requirements

Thus far, we have largely ignored the question of when HAT semantics are useful (or otherwise are too weak). As we showed in Section 5, the main cost of high availability and low latency comes in the inability to prevent Lost Update, Write Skew, and provide recency bounds. In this section, we attempt to understand when these guarantees matter both abstractly and in a representative transactional application based on the TPC-C benchmark [67].

Commutativity and Monotonicity As evidenced by the CALM Theorem [4] and by Commutative and Replicated Data Types [63], if updates logically commute, then they can often be safely performed in different orders at different replicas. Accordingly, as long as all writes are delivered to all replicas, then a system executing monotonic logic may not suffer from application-level consistency anomalies as a result of Lost Update or Write Skew anomalies. However, applications with non-monotonic state mutation will not, in general, be able to maintain application-level consistency constraints with HATs alone—in particular, applications requiring bounded update visibility latency should opt for unavailability.

TPC-C To better understand the impact of HAT-compliance in an application context, we consider a concrete application: the TPC-C benchmark. In brief, we find that four of five transactions can be executed with HATs, while the fifth may require unavailability.

TPC-C consists of five transactions, capturing the operation of a wholesale warehouse, including sales, payments, and deliveries. Two transactions—*Order-Status* and *Stock-Level*—are read-only and can be executed safely with HATs. Clients may read stale data, but this does not violate TPC-C requirements and clients will read their writes if they are sticky-available. Another transaction type, *Payment*, updates running balances for warehouses, districts, and customer records and provides an audit trail. The transaction is monotonic—increment- and append-only—so all balance increase operations commute, and TA allows the maintenance of foreign-key integrity constraints (e.g., via UPDATE/DELETE CASCADE).

New-Order and Delivery. While three out of five transactions are easily achievable with HATs, the remaining two transactions are not as simple. The New-Order transaction places an order for a variable quantity of data items, updating warehouse stock as needed. It selects a sales district, assigns the order an ID number, adjusts the remaining warehouse stock, and writes a placeholder entry for the pending order. The Delivery transaction represents the fulfillment of a New-Order: it deletes the order from the pending list, updates the customer’s balance, updates the order’s carrier ID and delivery time, and updates the customer balance.

IDs and decrements. The New-Order transaction presents two challenges: ID assignment and stock maintenance. First, each New-Order transaction requires a unique ID number for the order. We can create a unique number by, say, concatenating the client ID and a timestamp. However, the TPC-C specification requires order numbers to be *sequentially* assigned within a district, which requires preventing Lost Update. Accordingly, HATs cannot provide compliant TPC-C execution but can still maintain uniqueness constraints. Second, the New-Order transaction decrements inventory counts: what if the count becomes negative? Fortunately, TPC-C New-Order restocks each item’s inventory count (increments by 91) if it would become negative as the result of placing an order. This means that, even in the presence of concurrent New-Orders, an item’s stock will never fall below zero. This is TPC-C compliant, but a HAT system might end up with more stock than in a non-HAT-compliant implementation.

TPC-C Non-monotonicity. The Delivery transaction is challenging due to non-monotonicity. Each Delivery deletes a pending order from the New-Order table and should be idempotent in order to avoid billing a customer twice; this implies a need to prevent Lost Update. This issue can be avoided by moving the non-monotonicity to the real world—the carrier that picks up the package for an order can ensure that no other carrier will do so—but cannot provide a correct execution with HATs alone. However, according to distributed transaction architects [43], these compensatory actions are relatively common in real-world business processes.

Integrity Constraints. Throughout execution, TPC-C also requires the maintenance of several integrity constraints. For example, Consistency Condition 1 (3.3.2.1) requires that each warehouse’s sales count must reflect the sum of its subordinate sales districts. This integrity constraint spans two tables but, given the ability to update rows in both tables atomically via TA, can be easily maintained. Consistency Conditions 4 through 12 (3.3.2.4–12) can similarly be satisfied by applying updates atomically across tables. Consistency Conditions 2 and 3 (3.3.2.2–3) concern order ID assignment and are problematic. Finally, while TPC-C is not subject to multi-key anomalies, we note that many TPC-E isolation tests (i.e., simultaneously modifying a product description and its thumbnail) are also achievable using HATs.

Summary. Many—but not all—TPC-C transactions are well-served

by HATs. The two problematic transactions, New-Order and Payment, rely on non-monotonic state update. The former can be modified to ensure ID uniqueness but not sequential ID ordering, while the latter is inherently non-monotonic, requiring external compensation or stronger consistency protocols. Based on these experiences and discussions with practitioners, we expect that, especially for read-dominated workloads found in many online services, HAT guarantees will provide useful semantics for many applications.

6.3 Experimental Costs

To further understand the performance implications of HAT guarantees in a real-world environment, we implemented a HAT database prototype. Across a range of deployments on public cloud infrastructures, we found that, as Section 2.2’s measurements suggested, “strongly consistent” algorithms incur substantial latency penalties: over WAN, 10 to 100 times higher than their HAT counterparts. Given recent algorithms for providing causal consistency [9, 52, 73], we focus our HAT analysis on TA (algorithm from Section 5.1.2, described in greater detail in our Technical Report [7]), which we believe to be the most interesting of our algorithms. We find that HAT properties—while more resource-intensive than basic eventual consistency—scale well to many servers.

Implementation. Our prototype database is a partially replicated (hash-based, partitioned) key-value backed by LevelDB and implemented in Java using Apache Thrift. It currently supports eventual consistency (hereafter, *eventual*; last-writer-wins RU with standard all-to-all anti-entropy between replicas) and HAT RC and TA with RC guarantees (hereafter, *TA*). It also supports non-HAT operation whereby all operations for a given key are routed to a (randomly) designated master replica for each key (hereafter, *master*; i.e., PNUTS [23]) as well as distributed two-phase locking. Servers are durable: they synchronously write to LevelDB before responding to client requests, while new writes in TA are sent to a write-ahead log, which is synchronously flushed to disk.

Configuration. We deploy the database in *clusters*—disjoint sets of database servers that each contain a single, fully replicated copy of the data—typically across datacenters, sticking all clients within a datacenter to their respective cluster (trivially providing read-your-writes and monotonic reads guarantees). By default, we use 5 Amazon EC2 m1.xlarge instances as servers in each cluster. For our workload, we link our client library to the YCSB benchmark [24], which is well-suited to LevelDB’s key-value schema, grouping every eight YCSB operations from the default workload (50% reads, 50% writes) to form a transaction. We increase the number of keys in the workload from the default 1,000 to 100,000 with uniform random key access, keeping the default value size of 1KB, and running YCSB for 180 seconds per configuration.

Geo-replication. We first deploy the database prototype across an increasing number of datacenters. Figure 3A shows that, when operating two clusters within a single datacenter, mastering each data item results in approximately half the throughput and double the latency of *eventual*. This is because HAT models are able to utilize replicas in both clusters instead of always contacting the (single) master. RC—essentially *eventual* with buffering—is almost identical to *eventual*, while TA—which incurs two writes for every client-side write (i.e., new writes are sent to the WAL then subsequently moved into LevelDB once pending stable)—achieves 75% of the throughput. Latency increases linearly with the number of YCSB clients due to contention within LevelDB.

In contrast, when the two clusters are deployed across the continental United States (Figure 3B), the average latency of master increases to 300ms (a 278–4257% latency increase; average 37ms la-

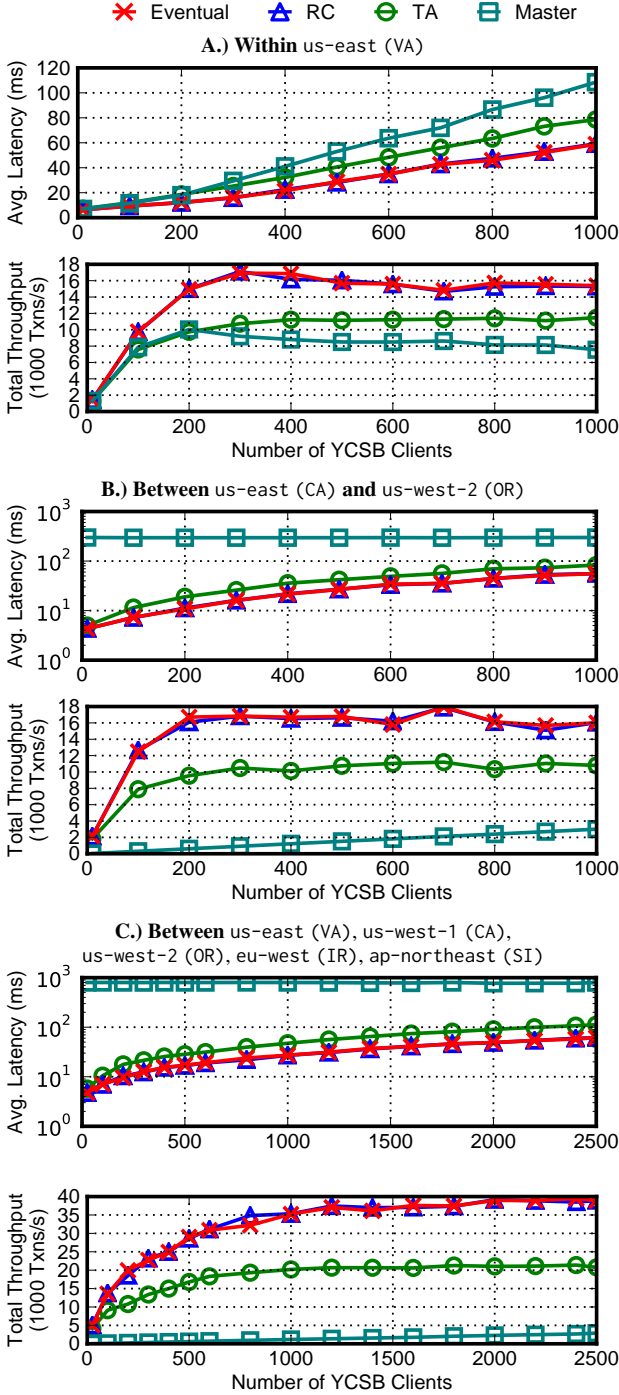


Figure 3: YCSB performance for two clusters of five servers each deployed within a single datacenter and cross-datacenters.

tency per operation). For the same number of YCSB client threads, master has substantially lower throughput than the HAT configurations. Increasing the number of YCSB clients *does* increase the throughput of master, but our Thrift-based server-side connection processing did not gracefully handle more than several thousand concurrent connections. In contrast, across two datacenters, the performance of eventual, RC, and TA are near-identical to a single-datacenter deployment.

When five clusters (as opposed to two, as before) are deployed

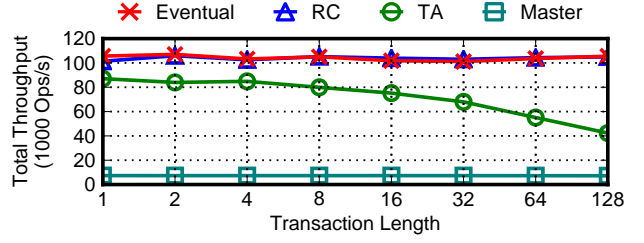


Figure 4: Transaction length versus throughput.

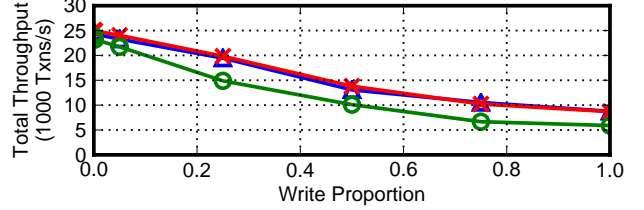


Figure 5: Proportion of reads and writes versus throughput.

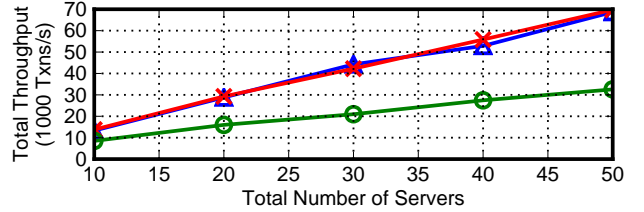


Figure 6: Scale-out of TA, Eventual, and RC.

across the five EC2 datacenters with lowest communication cost (Figure 3C), the trend continues: master latency increases to nearly 800ms per transaction. As an attempt at reducing this overhead, we implemented and benchmarked a variant of quorum-based replication as in Dynamo [31], where clients sent requests to all replicas, which completed as soon as a majority of servers responded (guaranteeing regular semantics [44]); this strategy (not pictured) did not substantially improve performance due to the network topology and because worst-case server load was unaffected. With five clusters, TA’s relative throughput decreased: every YCSB put operation resulted in four put operations on remote replicas and, accordingly, the cost of anti-entropy increased (e.g., each server processed four replica’s anti-entropy as opposed to one before, reducing the opportunity for batching and decreasing available resources for incoming client requests). This in turn increased garbage collection activity and, more importantly, IOPS when compared to Eventual and RC, causing TA throughput to peak at around half of Eventual. With in-memory persistence (i.e., no LevelDB or WAL), TA throughput was within 20% of eventual.

We have intentionally omitted performance data for two-phase locking. master performed *far* better than our textbook implementation, which, in addition to requiring a WAN round-trip per operation, also incurred substantial overheads due to mutual exclusion via locking. We expect that, while techniques like those recently proposed in Calvin [66] can reduce the overhead of serializable transactions by avoiding locking, our mastered implementation and the data from Section 2.2 are reasonable lower bounds on latency.

Transaction length. As shown in Figure 4 (clusters in Virginia and Oregon), throughput of eventual, RC, and master operation are unaffected by transaction length. In contrast, TA throughput decreases linearly with increased transaction length: with 1 operation per transaction, TA throughput is within 18% of eventual (34 bytes overhead), and with 128 operations per transaction, TA throughput

is within 60% (1898 bytes overhead). This reflects our TA algorithm’s metadata requirements, which are proportional to transaction length and consume IOPS and network bandwidth.

Read proportion. Our default (equal) proportion of reads and writes is fairly pessimistic: for example, Facebook reports 99.8% reads for their workload [53]. As shown in Figure 5 (clusters in Virginia and Oregon), with all reads, TA is within 4.8% of eventual; with all writes, TA is within 33%, and the throughput of eventual decreases by 288.8% compared to all reads. At 99.8% reads, TA incurs a 7% overhead (5.8% for in-memory storage).

Scale-out. One of the key benefits of our HAT algorithms is that they are shared-nothing, meaning they should not compromise scalability. Figure 6 shows that varying the number of servers across two clusters in Virginia and Oregon (with 15 YCSB clients per server) results in linear scale-out for eventual, RC, and TA. RC and eventual scale perfectly with an approximately 5x throughput increase moving from 5 to 25 servers per cluster. For the same configuration, TA scales by 3.8x, achieving over 260,000 operations per second. TA performance is due to resource contention—with a memory-backed database (instead of LevelDB), TA scales by 4.25x (not shown)—and TA-related performance heterogeneity across servers (Calvin’s authors report similar heterogeneity on EC2 [66]). Nevertheless, this linear scalability is not typical of traditional database system designs [41].

Summary. Our experimental prototype confirms our earlier analytical intuitions. HAT systems can provide useful semantics without substantial performance penalties. In particular, our TA algorithm can achieve throughput competitive with eventual consistency at the expense of increased disk and network utilization. Perhaps more importantly, all HAT algorithms circumvent high WAN latencies inevitable with non-HAT implementations. Our results highlight Deutsch’s observation that ignoring factors such as latency can “cause big trouble and painful learning experiences” [33]—in a single-site context, paying the cost of coordination may be tenable, but, especially as services are geo-replicated, costs increase.

7 Related Work

While we have discussed traditional mechanisms for distributed coordination and several related systems in Section 6.1, in this section, we further discuss related work. In particular, we discuss related work on highly available semantics, mechanisms for concurrency control, and techniques for scalable distributed operations.

Weak consistency and high availability have been well studied. Serializability has long been known to be unachievable [29] and Brewer’s CAP Theorem has attracted considerable attention [38]. Recent work on PACELC expands CAP by considering connections between “weak consistency” and low latency [1], while several studies examine weak isolation guarantees [2, 11]. However, as we have discussed, the connection between weak, multi-object consistency models in a distributed setting and high availability is relatively unexplored. With the exception of our preliminary workshop paper discussing transactional availability, real-world ACID, and HAT RC and I-CI [8]—which this work expands, providing additional algorithms and impossibility results, a full taxonomization, experimental and application analysis, and much greater discussion of implications and related work—we believe this paper is the first to explore this area. However, several studies rigorously classify *non-HAT* semantics: Wisemann et al. have proposed a three parameter classification for one-copy serializable database systems, performing a more extensive classification than our overview in

Section 6, including eager database replication techniques [71] and distributed mechanisms for achieving one-copy serializability [72].

There has been a recent resurgence of interest in distributed multi-object semantics, both in academia [13, 26, 47, 53, 64, 66, 73] and industry [17, 25]. As discussed in Section 3, classic ACID databases provide strong semantics but their lock-based and traditional multi-versioned implementations are unavailable in the presence of partitions [12, 41]. Notably, Google’s Spanner provides strong one-copy serializable transactions. While Spanner is highly specialized for Google’s read-heavy workload, it relies on two-phase commit and two-phase locking for read/write transactions [25]. As we have discussed, the latency penalties associated with this design choice are fundamental to serializability. For users willing to tolerate these costs, Spanner, or similar strongly consistent, unavailable systems—including Calvin [66], G-Store [26], Generalized Snapshot Isolation [35], HBase, HStore [45], MDCC [47], Orleans [17], Postgres-R [46], Walter [64], and a range of snapshot isolation techniques [18, 50, 28]—are a reasonable choice.

With HATs, we seek an alternative set of semantics that are still useful but do not violate requirements for high availability or low latency. Recent systems proposals such as Swift [73], Eiger [53], and Bolt-on Causal Consistency [9] provide transactional causal consistency guarantees with varying availability and represent a new class of sticky HAT systems. There are infinitely many HAT models (i.e., always reading value 1 is comparable with always returning value 2), but a recent report from UT Austin shows that no model stronger than causal consistency can be achieved in a sticky highly available, *one-way convergent* system [54]. This result is promising and complementary to our results for general-purpose convergent data stores. Finally, Burkhardt et al. have concurrently developed an axiomatic specification for eventually consistent stores; their work-in-progress report contains alternate formalism for several HAT guarantees and (snapshot) transactions [16].

8 Conclusions and Future Work

The current state of database software offers uncomfortable and unnecessary choices between availability and transactional semantics. Through our analysis and experiments, we have demonstrated how goals of high availability will remain a critical aspect of many future data storage systems. Accordingly, we expose a broad design space of Highly Available Transactions (HATs), which can offer the key benefits of highly available distributed systems—“always on” operation during partitions and low-latency operations—while also providing a family of transactional isolation levels and replica semantics that have been adopted in practice. In taxonomizing this design space, we show that many transactional guarantees are achievable with high availability, while a few, like preventing Lost Update and Write Skew, are not. This offers a useful connection between storage semantics studied in the database and distributed systems communities.

HATs raise several challenges for future study. In this paper, we have highlighted standardized models, but we would like a more concise description of which models are and are not achievable in HAT systems. Similarly, while we have studied the analytical and experiment behavior of several HAT models, there is substantial work in further understanding the performance and design of systems within the large set of HAT models. We also believe it is time to revisit techniques such as Sagas [37] and other long-running transaction support in order to aid HAT programming. Weakened failure assumptions as in escrow or in the form of bounded network asynchrony could enable richer HAT semantics at the cost of general-purpose availability. Alternatively, there is a range of possible hybrid systems providing strong semantics during partition-

free periods and weakened semantics during partitions. Based on our understanding of what is desired in the field and newfound knowledge of what is possible to achieve, we believe HATs provide a large and useful design space for exploration.

9 References

- [1] D. J. Abadi. Consistency tradeoffs in modern distributed database system design: CAP is only part of the story. *IEEE Computer*, 45(2), 2012.
- [2] A. Adya. *Weak consistency: a generalized theory and optimistic implementations for distributed transactions*. PhD thesis, MIT, 1999.
- [3] M. Ahamad, G. Neiger, J. E. Burns, P. Kohli, and P. Hutto. Causal memory: Definitions, implementation and programming. *Dist. Comp.*, 9(1), 1995.
- [4] P. Alvaro, N. Conway, J. M. Hellerstein, and W. R. Marczak. Consistency analysis in Bloom: a CALM and collected approach. In *CIDR 2011*.
- [5] ISO/IEC 9075-2:2011 *Information technology – Database languages – SQL – Part 2: Foundation (SQL/Foundation)*.
- [6] AWS. Summary of the Amazon EC2 and Amazon RDS Service Disruption in the US East Region. <http://tinyurl.com/6ab6e16>, April 2011.
- [7] P. Bailis, A. Davidson, A. Fekete, A. Ghodsi, J. M. Hellerstein, and I. Stoica. Highly Available Transactions: Virtues and Limitations (Extended). Technical report. <http://bailis.org/private/hat-extended.pdf>.
- [8] P. Bailis, A. Fekete, A. Ghodsi, J. M. Hellerstein, and I. Stoica. HAT, not CAP: Introducing Highly Available Transactions. In *To appear in HotOS 2013*. N.B.: version appearing on the arXiv is a superset of workshop paper.
- [9] P. Bailis, A. Ghodsi, J. M. Hellerstein, and I. Stoica. Bolt-on causal consistency. In *SIGMOD 2013*.
- [10] barrkel. Hacker News comment thread. <http://tinyurl.com/bmrjo7y>, 2009. (Anecdotal but unequivocal.)
- [11] H. Berenson, P. Bernstein, J. Gray, J. Melton, E. O’Neil, and P. O’Neil. A critique of ANSI SQL isolation levels. In *SIGMOD 1995*.
- [12] P. Bernstein, V. Hadzilacos, and N. Goodman. *Concurrency control and recovery in database systems*, volume 370. Addison-wesley New York, 1987.
- [13] M. Brantner, D. Florescu, D. Graf, D. Kossmann, and T. Kraska. Building a database on S3. In *SIGMOD 2008*.
- [14] E. Brewer. Towards robust distributed systems. Keynote at PODC 2000.
- [15] J. Brzezinski, C. Sobaniec, and D. Wawrzyniak. From session causality to causal consistency. In *PDP 2004*.
- [16] S. Burckhardt, A. Gotsman, and H. Yang. Understanding eventual consistency. Technical Report MSR-TR-2013-39. <http://tinyurl.com/bqty9yz>.
- [17] S. Bykov, A. Geller, G. Klier, J. R. Larus, R. Pandya, and J. Thelin. Orleans: cloud computing for everyone. In *SOCC 2011*.
- [18] E. Cecchet, G. Candea, and A. Ailamaki. Middleware-based database replication: the gaps between theory and practice. In *SIGMOD 2008*.
- [19] A. Chan and R. Gray. Implementing distributed read-only transactions. *IEEE Transactions on Software Engineering*, (2):205–212, 1985.
- [20] F. Chang, J. Dean, S. Ghemawat, et al. Bigtable: A distributed storage system for structured data. In *OSDI 2006*.
- [21] B. Charron-Bost. Concerning the size of logical clocks in distributed systems. *Inf. Process. Lett.*, 39(1), 1991.
- [22] G. Clarke. The Register: NoSQL’s CAP theorem busters: We don’t drop ACID. <http://tinyurl.com/bpsug4b>, November 2012.
- [23] B. Cooper et al. PNUTS: Yahoo!’s hosted data serving platform. In *VLDB 2008*.
- [24] B. F. Cooper, A. Silberstein, E. Tam, R. Ramakrishnan, and R. Sears. Benchmarking cloud serving systems with YCSB. In *ACM SOCC 2010*.
- [25] J. C. Corbett, J. Dean, M. Epstein, A. Fikes, C. Frost, J. J. Furman, et al. Spanner: Google’s globally-distributed database. In *OSDI 2012*.
- [26] S. Das, D. Agrawal, and A. El Abbadi. G-store: a scalable data store for transactional multi key access in the cloud. In *SOCC 2010*, pages 163–174.
- [27] K. Daudjee and K. Salem. Lazy database replication with ordering guarantees. In *ICDE 2004*, pages 424–435.
- [28] K. Daudjee and K. Salem. Lazy database replication with snapshot isolation. In *VLDB 2006*, pages 715–726.
- [29] S. Davidson, H. Garcia-Molina, and D. Skeen. Consistency in partitioned networks. *ACM CSUR*, 17(3):341–370, 1985.
- [30] J. Dean. Designs, lessons and advice from building large distributed systems. Keynote at LADIS 2009.
- [31] G. DeCandia, D. Hastorun, M. Jampani, G. Kakulapati, A. Lakshman, et al. Dynamo: Amazon’s highly available key-value store. In *SOSP 2007*.
- [32] A. Demers, D. Greene, C. Hauser, W. Irish, J. Larson, S. Shenker, H. Sturgis, D. Swinehart, and D. Terry. Epidemic algorithms for replicated database maintenance. In *PODC*, pages 1–12, 1987.
- [33] P. Deutsch. The eight fallacies of distributed computing. <http://tinyurl.com/c6vvtzg>, 1994.
- [34] R. Dillet. Update: Amazon Web Services down in North Virginia Reddit, Pinterest, Airbnb, Foursquare, Minecraft and others affected. TechCrunch <http://tinyurl.com/9r43dwt>, October 2012.
- [35] S. Elnikety, W. Zwaenepoel, and F. Pedone. Database replication using generalized snapshot isolation. In *SRDS 2005*, pages 73–84.
- [36] A. Fekete, D. Liarokapis, E. O’Neil, P. O’Neil, and D. Shasha. Making snapshot isolation serializable. *ACM TODS*, 30(2):492–528, June 2005.
- [37] H. Garcia-Molina and K. Salem. Sagas. In *SIGMOD 1987*.
- [38] S. Gilbert and N. Lynch. Brewer’s conjecture and the feasibility of consistent, available, partition-tolerant web services. *SIGACT News*, 33(2):51–59, 2002.
- [39] P. Gill, N. Jain, and N. Nagappan. Understanding network failures in data centers: measurement, analysis, and implications. In *SIGCOMM 2011*.
- [40] J. Gray. The transaction concept: Virtues and limitations. In *VLDB 1981*.
- [41] J. Gray, R. Lorie, G. Putzolu, and I. Traiger. Granularity of locks and degrees of consistency in a shared data base. Technical report, IBM, 1976.
- [42] J. Hamilton. Stonebraker on CAP Theorem and Databases. <http://tinyurl.com/d3gtfq9>, April 2010.
- [43] P. Helland. Life beyond distributed transactions: an apostate’s opinion. In *CIDR 2007*.
- [44] M. Herlihy and N. Shavit. *The art of multiprocessor programming*. 2008.
- [45] R. Kallman, H. Kimura, J. Natkins, A. Pavlo, A. Rasin, S. Zdonik, E. P. Jones, S. Madden, M. Stonebraker, Y. Zhang, et al. H-store: a high-performance, distributed main memory transaction processing system. In *VLDB 2008*.
- [46] B. Kemme. *Database replication for clusters of workstations*. PhD thesis, EPFL, 2000.
- [47] T. Kraska, G. Pang, M. Franklin, and S. Madden. MDCC: Multi-data center consistency. In *EuroSys 2013*.
- [48] K. Krikellas, S. Elnikety, Z. Vagena, and O. Hodson. Strongly consistent replication for a bargain. In *ICDE 2010*, pages 52–63.
- [49] C. Labovitz, A. Ahuja, and F. Jahanian. Experimental study of internet stability and backbone failures. In *FTCS 1999*.
- [50] Y. Lin, B. Kemme, R. Jiménez-Peris, M. Patiño-Martínez, and J. E. Armendáriz-Iñigo. Snapshot isolation and integrity constraints in replicated databases. *ACM TODS*, 34(2), 2009.
- [51] V. Liu, D. Halperin, A. Krishnamurthy, and T. Anderson. F10: Fault tolerant engineered networks. In *NSDI 2013*.
- [52] W. Lloyd, M. J. Freedman, M. Kaminsky, and D. G. Andersen. Don’t settle for eventual: scalable causal consistency for wide-area storage with COPS. In *SOSP 2011*.
- [53] W. Lloyd, M. J. Freedman, M. Kaminsky, and D. G. Andersen. Stronger semantics for low-latency geo-replicated storage. In *NSDI 2013*.
- [54] P. Mahajan, L. Alvisi, and M. Dahlin. Consistency, availability, convergence. Technical Report TR-11-22, CS Department, UT Austin, May 2011.
- [55] A. Markopoulou, G. Iannaccone, S. Bhattacharyya, C.-N. Chuah, Y. Ganjali, and C. Diot. Characterization of failures in an operational IP backbone network. *IEEE/ACM TON*, 16(4).
- [56] D. McCullagh. How Pakistan knocked YouTube offline (and how to make sure it never happens again). CNET, <http://tinyurl.com/c4pffd>, February 2008.
- [57] R. McMillan. Research experiment disrupts internet, for some. Computerworld, <http://tinyurl.com/23sqpek>, August 2010.
- [58] P. P. S. Narayan. Sherpa update. YDN Blog, <http://tinyurl.com/c3ljuce>, June 2010.
- [59] F. Pedone and R. Guerraoui. On transaction liveness in replicated databases. In *Pacific Rim International Symposium on Fault-Tolerant Systems*, 1997.
- [60] M. Raynal, G. Thia-Kime, and M. Ahamad. From serializable to causal transactions for collaborative applications. In *EUROMICRO 1997*.
- [61] A. Schiper and M. Raynal. From group communication to transactions in distributed systems. *CACM*, 39(4), 1996.
- [62] L. Segall. Internet routing glitch kicks millions offline. CNNMoney, <http://tinyurl.com/cmqqac3>, November 2011.
- [63] M. Shapiro, N. Preguiça, C. Baquero, and M. Zawirski. A comprehensive study of convergent and commutative replicated data types. INRIA TR 7506, 2011.
- [64] Y. Sovran, R. Power, M. K. Aguilera, and J. Li. Transactional storage for geo-replicated systems. In *SOSP 2011*.
- [65] D. B. Terry, A. J. Demers, K. Petersen, M. J. Spreitzer, M. M. Theimer, et al. Session guarantees for weakly consistent replicated data. In *PDIS 1994*.
- [66] A. Thomson, T. Diamond, S. Weng, K. Ren, P. Shao, and D. Abadi. Calvin: Fast distributed transactions for partitioned database systems. In *SIGMOD 2012*.
- [67] TPC Council. TPC Benchmark C revision 5.11, 2010.
- [68] D. Turner, K. Levchenko, J. C. Mogul, S. Savage, and A. C. Snoeren. On failure in managed enterprise networks. HP Labs HPL-2012-101, 2012.
- [69] D. Turner, K. Levchenko, A. C. Snoeren, and S. Savage. California fault lines: understanding the causes and impact of network failures. *SIGCOMM 2011*.
- [70] W. Vogels. Eventually consistent. *CACM*, 52(1):40–44, Jan. 2009.
- [71] M. Wiesmann, F. Pedone, A. Schiper, B. Kemme, and G. Alonso. Database replication techniques: A three parameter classification. In *SRDS 2000*.
- [72] M. Wiesmann, F. Pedone, A. Schiper, B. Kemme, and G. Alonso. Understanding replication in databases and distributed systems. In *ICDCS 2000*.
- [73] M. Zawirski, A. Bieniusa, V. Balesar, N. Preguiça, S. Duarte, M. Shapiro, and C. Baquero. Geo-replication all the way to the edge. Personal communication and draft under submission. <http://tinyurl.com/cp68svy>.