Disciplined Inconsistency

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Submission Type: Research

Abstract

Distributed applications and web services, such as online stores or social networks are expected to be scalable, always available, respond quickly to users around the world, and never lose data. To meet these steep requirements in the face of high round-trip latencies, network partitions, server failures, and load spikes, applications use eventually consistent datastores that allow them to weaken the consistency of some data. However, making this transition is highly error-prone because relaxed consistency models are notoriously difficult to understand and test.

In this work, we propose a new programming model for distributed data that makes consistency properties explicit and uses a type system to enforce *consistency safety*. With the *Inconsistent Performance-bound Approximate* (IPA) storage system, programmers specify performance targets and correctness requirements as constraints on persistent data structures and handle uncertainty about the result of datastore reads using new *consistency types*. We implement a prototype of this model in Scala on top of an existing datastore, Cassandra and use it to make performance/correctness tradeoffs in two applications: a ticket sales service and a Twitter clone. Our evaluation shows that IPA helps prevent consistency-based programming errors, adapts consistency automatically in response to changing network conditions, and performs comparably to weak consistency and 2-10× faster than strong consistency.

1. Introduction

To provide good user experiences, modern datacenter applications and web services must balance many competing requirements. Programmers need to preserve application correctness while minimizing response times; e.g., a web store must not double-charge for purchases and not keeping users waiting too long (e.g., Microsoft, Amazon and Google all note that every millisecond of latency translates to a loss in traffic and revenue [26, 36]). Worse, programmers must maintain this balance in an unpredictable environment where a black and blue dress [42] or Justin Bieber [38] can change application performance in the blink of an eye.

Recognizing this trade-off, many existing storage systems support configureable consistency levels; some allow programmers to set the consistency of the entire store or each operation [4, 11, 34, 58]. Ideally, programs would only weaken consistency guarantees when necessary to meet availability requirements (e.g., during a spike in traffic or datacenter failure), or when it does not impact the application's correctness guarantees (e.g., returning a slightly stale or estimated result is acceptable). Some storage systems support this type of adaptable consistency [59, 61]. Unfortunately, if programmers are *undisciplined* in their use of data from weakly consistent operations, they can corrupt strongly consistent stored data, lowering the consistency of the storage system to that of the weakest read or write operation.

In this paper, we propose a more disciplined approach to inconsistency in the *inconsistent, performance-bound, approximate (IPA)* storage system. IPA introduces the following concepts:

- *Consistency Safety*, a new property that ensures that values from weakly consistent operations cannot flow into stronger consistency operations without explicit endorsement from the programmer. IPA is the first storage system to provide consistency safety.
- *Consistency Types.*, a new type system for which *type safety implies consistency safety*. Consistency types define the consistency and correctness of the returned value from every IPA operation, allowing programmers to reason about their use of different consistency levels. IPA's type checker enforces the disciplined use of IPA consistency types statically at compile time by requiring programmers to handle all potential consistency cases, or explicitly endorse the propagation of inconsistent values.
- *Error-bounded Consistency*. IPA is a data structure store, like Redis [54] or Riak [11], allowing it to provide both traditional performance bounds on storage operations, as well as error bounds (e.g., the programmer can bound the returned value to within 5% of the correct value). Within these bounds, IPA automatically adapts to return a value with the strongest IPA consistency type possible under the current system load.

We implement an IPA prototype based on Scala and Cassandra and show that IPA allows the programmer to trade off performance and consistency, safe in the knowledge that the type system has checked the program for consistency safety. We demonstrate experimentally that these mechanisms allow applications to dynamically adapt correctness and performance to changing conditions with three applications: a simple counter, a Twitter clone based on Retwis [55] and a Ticket sales service modeled after FusionTicket [1].

2. The Case for Consistency Safety

Unpredictable Internet traffic and unexpected failures force modern datacenter applications to trade off consistency for performance. In this section, we demonstrate the pitfalls of doing so in an undisciplined way. As an example, we describe a movie ticketing service, similar to AMC or Fandango. Because ticketing services process financial transactions, they must ensure correctness, which they can do by storing their data in a strongly consistent storage system. Unfortunately, providing strong consistency for every storage operation can cause the storage system and application to collapse under high load, as several ticketing services did in October 2015, when tickets became available for the new Star Wars movie [21].

The IPA types encapsulate information about the consistency achieved when reading a value. Formally, the IPA types form a lattice parameterized by a primitive type `T`, shown in [#lattice]. Strong read operations return values of type `Consistent[T]` (the top element), and so (by implicit cast) behave as any other instance of type `T`. Intuitively, this equivalence is because the results of strong reads are known to be consistent, which corresponds to the control flow in conventional (non-distributed) applications. Weaker read operations return values of some type lower in the lattice (*weak IPA types*), reflecting their possible inconsistency. The bottom element `Inconsistent[T]` specifies an object with the weakest possible (or unknown) consistency. The other IPA types follow a subtyping relation $\prec$ as illustrated in [#lattice].

The only possible operation on `Inconsistent[T]` is to *endorse* it. Endorsement is an upcast, invoked by `Consistent(x)`, to the top element `Consistent[T]` from other types in the lattice:

$$\frac{\Gamma \vdash e_1 : \tau[T] \qquad T \prec \tau[T]}{\Gamma \vdash \text{Consistent}(e_1) : T}$$

The core type system statically enforces safety by preventing weaker values from flowing into stronger computations. Forcing developers to explicitly endorse inconsistent values prevents them from accidentally using inconsistent data there they did not determine it was acceptable, essentially inverting the behavior of current systems where inconsistent data is always treated as if it was safe to use anywhere. However, endorsing values blindly in this way is not the intended use case; the key productivity benefit of the IPA type system comes from the other IPA types which correspond to the consistency policies in §3.3 which allow developers to handle dynamic variations in consistency, which we describe next.

3.4.1. Rushed types

The weak IPA type `Rushed[T]` is the result of read operations performed on an ADT with consistency policy `LatencyBound(x)`. `Rushed[T]` is a *sum type*, with one variant per consistency level available to the implementation of `LatencyBound`. Each variant is itself an IPA type (though the variants obviously cannot be `Rushed[T]` itself). The effect is that values returned by a latency-bound object carry with them their actual consistency level. A result of type `Rushed[T]` therefore requires the developer to consider the possible consistency levels of the value.

For example, a system with geo-distributed replicas may only be able to satisfy a latency bound of 50 ms with a local quorum read. In this case, `Rushed[T]` would be the sum of three types `Consistent[T]`, `LocalQuorum[T]`, and `Inconsistent[T]`. A match statement destructures the result of a latency-bound read operation:

```
set.contains() match {
  case Consistent(x) => print(x)
  case LocalQuorum(x) => print(x+", locally")
  case Inconsistent(_) => print("unknown")
}
```

The application may want to react differently to a local quorum as opposed to a strongly or weakly consistent value. Note that because of the subtyping relation on IPA types, omitted cases can be matched by any type lower in the lattice, including the bottom element `Inconsistent(_)`; other cases therefore need only be added if the application should respond differently to them. This subtyping behavior allows applications to be portable between systems supporting different forms of consistency (of which there are many).

3.4.2. Interval types

The weak IPA type `Interval[T]` is the result of operations performed on an ADT with consistency policy `ErrorTolerance(x%)`. `Interval[T]` represents an interval of values within which the true (strongly consistent) result lies. The interval reflects uncertainty in the true value created by relaxed consistency, in the same style as work on approximate computing [15].

The key invariant of the `Interval[T]` type is that uses of the interval are *indistinguishable* from a linearizable order. Consider a `Set` with 100 elements. With linearizability, if we `add` a new element and then read the `size` (or if this ordering is otherwise implied), we *must* get back 101 (provided no other updates are occurring). However, if `size` is annotated with `ErrorTolerance(5%)`, then `size` could return intervals such as $[95, 105]$ or $[100, 107]$, so the client cannot tell if the add was incorporated. This frees the system to optimize to improve performance, such as by delaying synchronization. While any partially-ordered domain could be represented as an interval (e.g., a Set with partial knowledge of its members), in this work we consider only numeric types.

In the ticket sales example, the counter ADT's accuracy policy means that reads of the number of tickets return an Interval[Int]. If the interval is well above zero, then users can be assured that there are sufficient tickets remaining. In fact, because the interval is indistinguishable from a linearizable order, in the absence of other user actions, a subsequent purchase must succeed. On the other hand, if the interval overlaps with zero, then there is a chance that tickets could already be sold out, so users should be warned. Note that ensuring that tickets are not over-sold is a separate concern requiring a different form of enforcement, which we describe in §5. The relaxed consistency of the interval type allows the system to optimize performance in the common case where there are many tickets available, and dynamically adapt to contention when the ticket count diminishes.

4. Enforcing dynamic policies

The dynamic policies introduced in the previous section allow programmers to describe application-level correctness properties but they require new runtime mechanisms to enforce. But first, we briefly review consistency in Dynamo-style replicated systems.

To be sure of seeing a particular write, *strong* reads must coordinate with a majority (*quorum*) of replicas and compare their responses. For a write and read pair to be *strongly consistent* (in the CAP sense [17]), the replicas acknowledging the write (W) plus the replicas contacted for the read (R) must be greater than the total number of replicas ($W + R > N$). This can be achieved, for example, by writing to a quorum ($(N+1)/2$) and reading from a quorum (QUORUM in Cassandra), or writing to N (ALL) and reading from 1 (ONE) [22]. Cassandra also supports limited linearizable conditional updates and varying degrees of weaker consistency, particularly to handle different locality domains (e.g. LOCAL_QUORUM).

4.1. Latency bounds

The time it takes to achieve a particular level of consistency depends on current conditions and can vary over large time scales (minutes or hours) but can also vary significantly for individual operations. During normal operation, strong consistency may have acceptable performance while at peak traffic times the application would fall over. Latency bounds specified by the application allow the system to *dynamically* adjust to maintain comparable performance under varying conditions.

It is conceptually quite simple to implement a dynamically tunable consistency level: send read requests to as many replicas as necessary for strong consistency (depending on the strength of corresponding writes it could be to a quorum or all), but then when the latency time limit is up, take however many responses have been received and compute the most consistent response possible from them.

Unfortunately, Cassandra's client interface does not allow latency bounds exactly as described above: operations must specify a consistency level in advance. Instead, we issue read requests at different levels in parallel. We compose the parallel operations and respond either when the strong operation returns or with the strongest available result at the specified time limit. If no responses are available at the time limit, we wait for the first to return.

4.1.1. Monitors

The main problem with this approach is that it wastes a lot of work, even if we didn't need to duplicate some messages due to the client interface. Furthermore, if the system is responding slower due to a sudden surge in traffic, then it is essential that our efforts not cause additional burden on the system. In these cases, we should back off and only attempt weaker consistency. To do this, the system monitors current traffic and predicts the latency of different consistency levels.

Each client in the system has its own Monitor (though multi-threaded clients can share one). The monitor records the observed latencies of reads, grouped by operation and consistency level. The monitor uses an exponentially decaying reservoir to compute running percentiles weighted toward recent measurements, ensuring that its predictions continually adjust to current conditions.

Whenever a latency-bound operation is issued, it queries the monitor to determine the strongest consistency likely to be achieved within the time bound, then issues one request at that consistency level and a backup at the weakest level, or only weak if none can meet the bound. In §6.2.1 we show empirically that even simple monitors allow clients to adapt to changing conditions.

4.2. Error bounds

We implement error bounds by building on the concepts of *escrow* and *reservations* [27, 44, 48, 50]. These techniques have been used in storage systems to enforce hard limits, such as an account balance never going negative, while permitting concurrency. The idea is to set aside a pool of permissions to perform certain update operations (we'll call them *reservations* or *tokens*), essentially treating *operations* as a manageable resource. If we have a counter that should never go below zero, there could be a number of *decrement* tokens equal to the current value of the counter. When a client wishes to decrement, it must first acquire sufficient tokens before performing the update operation, whereas increments produce new tokens. The insight is that the coordination needed to ensure that there are never too many tokens can be done *off the critical path*: tokens can be produced lazily if there are enough around already, and most importantly for this work, they can be *distributed* among replicas. This means that replicas can perform some update operations safely without coordinating with any other replicas.

4.2.1. Reservation Server

Reservations require mediating requests to the datastore to prevent updates from exceeding the available tokens. Furthermore, each server must locally know how many tokens it has without synchronizing. We are not aware of a commercial datastore that supports custom mediation of requests and replica-local state, so we need a custom middleware layer to handle reservation requests, similar to other systems which have built stronger guarantees on top of existing datastores [8, 10, 57].

Any client requests requiring reservations are routed to one of a number of *reservation servers*. These servers then forward operations when permitted along to the underlying datastore. All persistent data is kept in the backing store; these reservation servers keep only transient state tracking available reservations. The number of reservation servers can theoretically be decoupled from the number of datastore replicas; our implementation simply colocates a reservation server with each datastore server and uses the datastore's node discovery mechanisms to route requests to reservation servers on the same host.

4.2.2. Enforcing error bounds

Reservations have been used previously to enforce hard global invariants in the form of upper or lower bounds on values [10], integrity constraints [9], or logical assertions [37]. However, enforcing error tolerance bounds presents a new design challenge because the bounds are constantly shifting. Consider a `Counter` with a 10% error bound, shown in Figure 2. If the current value is 100, then 10 increments can be done before anyone must be told about it. However, we have 3 reservation servers, so these 10 reservations are distributed among them, allowing each to do some increments without synchronizing. If only 10 outstanding increments are allowed, reads are guaranteed to maintain the 10% error bound.

In order to perform more increments after a server has exhausted its reservations, it must synchronize with the others, sharing its latest increments and receiving any changes of theirs. This is accomplished by doing a strong write (`ALL`) to the datastore followed by a read. Once that synchronization has completed, those 3 tokens become available again because the reservation servers all temporarily agree on the value (in this case, at least 102).

Read operations for these types go through reservation servers as well: the server does a weak read from any replica, then determines the interval based on how many reservations there are. For the read in Figure 2, there are 10 reservations total, but Server B knows that it has not used its local reservations, so it knows that there cannot be more than 6 and can return the interval $[100, 106]$.

4.2.3. Narrowing bounds

Error-tolerance policies give an *upper bound* on the amount of error; ideally, the interval returned will be more precise than the maximum error when conditions are favorable. The error bound determines the *maximum* number of reservations that can be allocated per instance. To allow a variable number of tokens, each ADT instance keeps a count of tokens allocated by each server, and when servers receive write requests, they increment their count to allocate tokens to use. Allocating must be done with strong consistency to ensure all servers agree, which can be expensive, so we use long leases (on the order of seconds) to allow servers to cache their allocations. When a lease is about to expire, it preemptively refreshes its lease in the background so that writes do not block.

For each type of update operation there may be a different pool of reservations. Similarly, there could be different error bounds on different read operations. It is up to the designer of the ADT to ensure that all error bounds are enforced with appropriate reservations. Consider a `Set` with an error tolerance on its `size` operation. This requires separate pools for `add` and `remove` to prevent the overall size from deviating by more than the bound in either direction, so the interval is $[v - \texttt{remove.delta}, v + \texttt{add.delta}]$ where v is the size of the set and `delta` computes the number of outstanding operations from the pool. In some situations, operations may produce and consume tokens in the same pool – e.g., `increment` producing tokens for `decrement` – but this is only allowable if updates propagate in a consistent order among replicas, which may not be the case in some eventually consistent systems.

5. Implementation

IPA is implemented mostly as a client-side library to an off-the-shelf distributed storage system, though reservations are handled by a custom middleware layer which mediates accesses to any data with error tolerance policies. Our implementation is built on top of Cassandra, but IPA could work with any replicated storage system that supports fine-grained consistency control, which many commercial and research datastores do, including Riak [11].

IPA's client-side programming interface is written in Scala, using the asynchronous futures-based Phantom [45] library for type-safe access to Cassandra data. Reservation server middleware is also built in Scala using Twitter's Finagle framework [63]. Communication is done between clients and Cassandra via prepared statements, and between clients and reservations servers via Thrift remote-procedure-calls [6]. Due to its type safety features, abstraction capability, and compatibility with Java, Scala has become popular for web service development, including widely-used frameworks such as Akka [35] and Spark [5], and at established companies such as Twitter and LinkedIn [2, 18, 29].

The IPA type system, responsible for consistency safety, is also simply part of our client library, simply leveraging Scala's sophisticated type system. The IPA type lattice is implemented as a subclass hierarchy of parametric classes, using Scala's support for higher-kinded types to allow them to be destructured in match statements, and implicit conversions to allow `Consistent[T]` to be treated as type `T`. We use traits to implement ADT annotations; e.g. when the `LatencyBound` trait is mixed into an ADT, it wraps each of the methods, redefining them to have the new semantics and return the correct IPA type. Figure 3 shows an example.

IPA comes with a library of reference ADT implementations used in our experiments, but it is intended to be extended with custom ADTs to fit more specific use cases. Our implementation provides a number of primitives for building ADTs, some of which are shown in Figure 3. To support latency bounds, there is a generic `LatencyBound` trait that provides facilities for executing a specified read operation at multiple consistency levels within a time limit. For implementing error bounds, IPA provides a generic reservation pool which ADTs can use. The library of reference ADTs includes:

- `Counter` based on Cassandra's counter, supporting increment and decrement, with latency and error bounds
- `BoundedCounter` CRDT from [10] that enforces a hard lower bound even with weak consistency. Our implementation adds the ability to bound error on the value of the counter and set latency bounds.
- `Set` with `add`, `remove`, `contains` and `size`, supporting latency bounds, and error bounds on `size`.
- `UUIDPool` generates unique identifiers, with a hard limit on the number of IDs that can be taken from it; built on top of `BoundedCounter` and supports the same bounds.
- `List`: thin abstraction around a Cassandra table with a time-based clustering order, supports latency bounds.

Figure 3 shows Scala code using reservation pools to implement a Counter with error bounds. The actual implementation splits this functionality between the client and the reservation server.

6. Evaluation

The goal of the IPA programming model and runtime system is to build applications that adapt to changing conditions, performing nearly as well as weak consistency but with stronger consistency and safety guarantees. To that end, we evaluate our prototype implementation under a variety of network conditions using both a real-world testbed (Google Compute Engine [28]) and simulated network conditions. We start with simple microbenchmarks to understand the performance of each of the runtime mechanisms independently. We then study two applications in more depth, exploring qualitatively how the programming model helps avoid potential programming mistakes in each and then evaluating their performance against strong and weakly consistent implementations.

6.1. Simulating adverse conditions

Evaluating replicated datastores under adverse conditions is challenging: tests conducted in a well-controlled environment where network latencies are low and variability is negligible will yield little of interest, whereas tests in production environments involve so many free variables that deciphering the results and reproducing them is difficult. An alternative approach is to *simulate* a variety of environments chosen to stress the system or mimic real challenging situations. We perform our experiments with a number of simulated conditions, and then validate our findings against experiments run on globally distributed machines in Google Compute Engine.

On our own test cluster with nodes linked by standard ethernet, we use Linux's Network Emulation facility [62] (`tc netem`) to introduce packet delay and loss at the operation system level. We use Docker containers [24] to enable fine-grained control of the network conditions between processes on the same physical node.

Table 1 shows the set of conditions we use in our experiments to explore the behavior of the system. We have a *uniform 5ms* condition to simulate latencies within a well-provisioned datacenter, *slow replica* which models imbalanced load or hardware problems that can cause one replica to be significantly slower to respond, and a condition mimicking geo-replication, with latency distributions based on measurements of latencies between virtual machines in the U.S., Europe, and Asia on Amazon EC2 [3]. These simulated conditions are validated by experiments with real networks in Google Compute Engine, running virtual machines in four datacenters: the client in *us-east*, and the datastore replicas in *us-central*, *europe-west*, and *asia-east*. We elide the results for *Local* (same rack in our own testbed) except in Figure 10 because the differences between policies are negligible. In such situations, strong consistency ought to be the default.

6.2. Microbenchmark: Counter

We start by measuring the performance of a very simple application that randomly increments and reads from a number of counters with different IPA policies. Random operations (`incr(1)` and `read`) are uniformly distributed over 100 counters from a single multithreaded client (allowing up to 4000 concurrent operations).

6.2.1. Latency bounds

Latency bounds aim to provide predictable performance for clients while attempting to maximize consistency. Under favorable conditions — when latencies and load are low — it is often possible to achieve strong consistency. Figure 4 shows the average latency of a counter with strong, weak, and two latency bounds under various conditions. We can see that there is a significant difference in latency between strong and weak. In these conditions, it is almost never possible to get strong consistency within 10ms, so the 10ms bound's monitor predicts it will not get strong consistency and falls back to weak consistency. For a 50ms bound, the counter is able to get strong consistency if network latency is low. However, with one slow replica (out of 3), there is a chance that the `QUORUM` read needed for strong consistency will hit the slow replica, so IPA attempts both; in this case, 82% got strong consistency, and 18% timed out and went with weak. Finally, with our simulated geo-distributed environment, there are no 2 replicas within 50ms of our client, so strong consistency is never possible within our bounds; as a result, IPA adapts to only attempt weak in both cases.

Figure 5 shows the 95th percentile latencies of the same workload. We see that the tail latency of the 10ms bound is comparable to weak, though the 50ms bound guesses incorrectly occasionally for the case of the slow replica. We see a gap between latency-bound and weak in the geo-distributed case. This is because the `weak` condition uses weak reads *and* writes, while our rushed types, in order to have the option of getting strong reads without requiring a read of `ALL`, must do `QUORUM` writes.

6.2.2. Error bounds

This experiment determines the cost of enforcing error bounds using the reservation system described in §4.2, and to determine how tight error bounds can be while providing performance comparable to weak consistency. Reservations move synchronization off the critical path: by distributing write permissions among replicas, reads can get strong guarantees from a single replica. When evaluating the latency bounds, we considered only read latency because we didn't change the writes. Because reservations actually slow down writes, now we must consider both.

Figure 6a shows latencies for error bounds of 1%, 5%, and 10%, plotting the average of reads *and* increment operations because reads along would always be equivalent to weak. We see that tighter bounds increase latency because it forces more synchronization, which must use consistency of `ALL`. In most conditions, 5-10% error bounds have latency comparable to weak, except geo-distributed, where it seems that our implementation of reservations is not a good solution.

While we have verified that error-bounded reads remain within our defined bounds, we also wish to know what error occurs in practice without the bounds. We modified our benchmark to be able to observe the error from weak consistency by incrementing counters a predetermined amount and observing the value; results are shown in Figure 6b. We plot the percent error of weak and strong against the actual observed interval width for a 1% error bound, going from a read-heavy (1% increments) to write-heavy (all increments, except to check the value).

First, we find that the *mean* error is less than 1% – inconsistency is quite rare, though it may be higher in practice, when operations come from more than one client. However, even with this experiment, we see outliers with significant error when writing is heavy: up to 60% error in the geo-replicated case. Finally, it is worth noting that for read-heavy workloads, the interval width (green line) is less than 1% because it dynamically adjusted as reservations were not needed.

6.3. Applications

Next, we explore the implementation of two applications in IPA and compare their performance with Cassandra using strictly strong or weak consistency on our simulated network testbed and Google Compute Engine.

6.3.1. Ticket service

Our Ticket sales web service, introduced in §2, is modeled after FusionTicket [1], which has been used as a benchmark in recent distributed systems research [65, 66]. We support the following actions:

- `browse`: List events by venue
- `viewEvent`: View the full description of an event including number of remaining tickets
- `purchase`: Purchase a ticket (or multiple)
- `addEvent`: Add an event at a venue.

Figure 7 shows a snippet of code from the IPA implementation which can be compared with the non-IPA version from Figure 1. Tickets are modeled using the `UUIDPool` type, which generates unique identifiers to reserve tickets for purchase. The ADT ensures that, even with weak consistency, it never gives out more than the maximum number of tickets, so it is safe to `endorse` the result of the `take` operation as long as one is okay with the possibility of a false negative. To compute the price of the reserved ticket, we now get back an `Interval` representing the range of possible remaining ticket counts, forcing our program to decide how to handle this range. We decide to use the `max` value from the interval to be conservative and fair to users; the 5% error bound ensures that we don't sacrifice too much profit this way.

To evaluate the performance, we run a workload modelling a typical small-scale deployment: 50 venues and 200 events, with an average of 2000 tickets each (gaussian distribution centered at 2000, stddev 500); this ticket-to-event ratio ensures that some events run out tickets. Because real-world workloads exhibit power law distributions [20], we use a moderately skewed Zipf distribution with coefficient of 0.6 to select events.

Figure 8 shows the average latency of a workload consisting of 70% viewEvent, 19% browse, 10% purchase, and 1% addEvent. We plot with a log scale because strong consistency has over 5× higher latency. The purchase event, though only 10% of the workload, drives most of the latency increase because of the work required to prevent over-selling tickets. We explore two different IPA implementations: one with a 20ms latency bound on all ADTs aiming to ensure that both viewEvent and browse complete quickly, and one where the ticket pool size ("tickets remaining") has a 5% error bound. We see that both perform with nearly the same latency as weak consistency. With the low-latency condition (*uniform* and *high load*), 20ms bound does 92% strong reads, 4% for *slow replica*, and all weak on both *geo-distributed* conditions.

Figure 8 also shows results on Google Compute Engine *(GCE)*. We see that the results of real geo-replication validate the findings of our simulated geo-distribution results.

On this workload, we observe that the 5% error bound performs well even under adverse conditions, which differs from our findings in the microbenchmark. This is because ticket UUIDPools begin *full*, with many tokens available, requiring less synchronization until they are close to running out. Contrast this with the microbenchmark, where counters started at small numbers (average of 500), where a 5% error tolerance means fewer tokens.

6.3.2. Twitter clone

Our second application is a Twitter-like service based on the Redis data modeling example, Retwis [55]. The data model is simple: each user has a Set of followers, and a List of tweets in their timeline. When a user tweets, the tweet ID is eagerly inserted into all of their followers' timelines. Retweets are tracked with a Set of users who have retweeted each tweet.

Figure 10 shows the data model, with dynamic policy annotations: latency bounds on followers and timelines. Retweets have an error bound on the size; this ensures that when tweets are displayed, the retweet count is not grossly inaccurate. As shown in the implementation of displayTweet, highly popular tweets with many retweets can tolerate approximate counts – they actually abbreviate the retweet count (e.g. "2.4M") – but average tweets, with less than 20 retweets, will get an exact count. This is important because for regular people, they will notice if a friend's retweet is not reflected in the count, whereas Ellen Degeneres's record-breaking celebrity selfie, which nearly brought down Twitter in 2014 [7], can scale because a 5% error tolerance on 3.4 million retweets provides significant slack.

The code for viewTimeline in Figure 10 demonstrates how latency-bound Rushed[T] types can be destructured with a match statement. In this case, the timeline (list of tweet IDs) is retrieved with a latency bound. Tweet content is added to the store before tweet IDs are pushed onto timelines, so with strong consistency we know that the list of IDs will all be able to load valid tweets. However, if the latency-bound type returns with weak consistency (Inconsistent case), then this *referential integrity* property may not hold. In that case, we must guard the call to displayTweet and retry if any of the operations fails if, for instance, the retweet set wasn't created yet.

For our performance evaluation, we simulate a realistic workload by generating a synthetic power-law graph, using a Zipf distribution to determine the number of followers per user. Our workload is a random mix with 50% timeline reads, 14% tweet, 30% retweet, 5% follow, and 1% newUser.

We see in Figure 11 that for all but the local (same rack) case, strong consistency is over 3× slower, but our implementation combining latency and error-bounds performs comparably with weak consistency, but with stronger guarantees for the programmer. Our simulated geo-distributed condition turns out to be the worst-case scenario for IPA's Twitter, with latency over 2× slower than weak consistency. This is because weak consistency performed noticeably better on our simulated network, which had one very close (1ms latency) replica that it could use almost exclusively.

7. Related Work

Consistency models. There is a thriving ecosystem of consistency models: from *sequential consistency* [33] and *linearizability* [30] on the strong side, to *eventual consistency* [64] at the other extreme. A variety of intermediate models fit elsewhere in the spectrum, each making different trade-offs balancing high performance and availability against ease of programming. Session guarantees, including *read-your-writes*, strengthen ordering for individual clients but reduce availability [60]. Many datastores support configuring consistency at a fine granularity: Cassandra [4] per operation, Riak [11] on an object or namespace granularity, as well as others [34, 58]. The Conit consistency model [67] breaks down the consistency spectrum into numerical error, order error, and staleness, but requires annotating each operation and explicit dependency tracking, rather than annotating ADTs.

Higher-level consistency requirements. Some programming models have gone beyond plain consistency models and allowed programmers to express correctness criteria directly. Quelea [57] has programmers write *contracts* to describe *visibility* and *ordering* constraints, independent of any particular consistency hierarchy, then the system automatically selects the consistency level necessary for each operation. In Indigo [9], programmers write *invariants* over abstract state and annotate post-conditions on actions in terms of the abstract state. The system analyzes annotated programs and adds coordination logic to prevent invariant violations, using a reservation system to enforce numer constraints. Neither Indigo nor Quelea, however, allow programmers to specify approximations or error tolerances, nor do they enforce any kind of performance bounds.

IPA's latency-bound policies were inspired by the *consistency-based SLAs* of Pileus [61]. Consistency SLAs specify a target latency and consistency level (e.g. 100 ms with read-my-writes), associated with a *utility*. Each operation specifies a set of SLAs, and the system predicts which is most likely to be met, attempting to maximize utility, and returns both the value and the achieved consistency level. Other systems, including PRACTI [12], PADS [13], and WheelFS [59], have given developers ways of expressing their desired performance and correctness requirements through *semantic cues* and policies.

A long history of systems have been built around the principle that applications may be willing to tolerate slightly stale data in exchange for improved performance, including databases [14, 46, 49, 51] and distributed caches [43, 47]. These systems generally require developers to explicitly specify staleness bounds on each transaction in terms of absolute time (although Bernstein et al.'s model can generate these from error bounds when a value's maximum rate of change is known).

The above techniques are relevant but largely orthogonal to our work: they provide many techniques which could be used in an IPA datastore to trade off correctness in new ways. This work builds on those insights, introducing a new error tolerance mechanism, proposing ADT-level annotations rather than per-operation, but most importantly, providing *type safety* via IPA types, which ensure that all possible edge cases are handled whenever the system adjusts consistency to meet performance targets. Previous systems gave some feedback to programs about achieved consistency, but did not provide facilities to ensure and help developers use the information correctly.

Types for distributed systems. *Convergent* (or *conflict-free*) *replicated data types* (CRDTs) [56] are data types designed for eventual consistency. Similar to how IPA types express weakened semantics which allow for implementation on weak consistency, CRDTs guarantee that they will converge on eventual consistency by forcing all update operations to commute. CRDTs can be useful because they allow concurrent updates with sane semantics, but they are still only eventually (or causally) consistent, so users must still deal with temporary divergence and out-of-date reads, and they do not incorporate performance bounds or variable accuracy. Particularly relevant to IPA, the Bounded Counter CRDT [10] enforces hard limits on the global value of a counter in a way similar to reservations but less general; this design informed our own reservations system for error bounds.

Types for approximation. IPA's type system is inspired by work on *approximate computing*, in which computations can be selectively made inaccurate to improve energy efficiency and performance. EnerJ [16, 53] and Rely [19, 39] track the flow of approximate values to prevent them from interfering with precise computation. IPA's interval types are similar to Uncertain<T>'s probability distributions [15] and to interval analysis [40]. One key difference for IPA is that inconsistent values can be strengthened by forcing additional synchronization if necessary. IPA also builds on information flow tracking systems [23, 41, 52], which use static type checking and dynamic analysis to enforce *non-interference* between sensitive data and untrusted channels.

8. Conclusion

The IPA programming model provides programmers with disciplined ways to trade consistency for performance in distributed applications. By specifying application-specific performance and accuracy targets in the form of latency and error tolerance bounds, they tell the system how to adapt when conditions change and provide it with release valves for optimization opportunities. Meanwhile, IPA types ensure consistency safety, ensuring that all potential weak outcomes are handled, and allowing applications to make choices based on the accuracy of the values the system returns. The policies, types and enforcement systems implemented in this work are only a sampling of the full range of possibilities within the framework of *inconsistent, performance-bound, and approximate* types.

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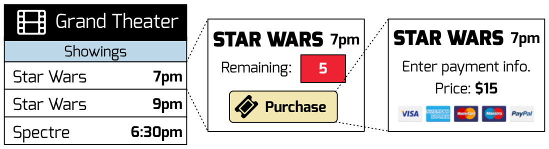


```
// adjust price based on number of tickets left
def computePrice(ticketsRemaining: Int): Float

def purchaseTicket(event: UUID) = {
  val ticket = reserveTicket(event)
  // weak read of ticket_count for performance
  val remaining = read_weak(event+"ticket_count")
  // compute price based on inconsistent read
  val price = computePrice(remaining)
  display("Enter payment info. Price: ", price)
}
```

To allow the application to scale more gracefully and han~dle traffic spikes, the programmer may chose to weaken the consistency of some operations. As shown in Figure [@fig-tickets], the ticket application displays each showing of the movie along with the number of tickets remaining. For better performance, the programmer may want to weaken the consistency of the read operation that fetches the remaining ticket count to give users an estimate, instead of the most up-to-date value. This policy would allow the storage system to return the precise number under normal load and something less precise (e.g., a value within the 5% of the actual value) under heavier traffic spikes.

While this solves the programmer's performance problem, it introduces data consistency problem. Suppose that the ticket sales application wants to raise the price of the last 100 tickets for each showing to $, similar to Uber's surge pricing. If the application uses a strongly consistent read to fetch the remaining ticket count, then it can use that value to compute the price of the ticket on the last screen in Figure [@fig-tickets]. However, if the programmer choses to weaken the consistency of that read, then he must be careful when using it to calculate a purchase. Done in an undisciplined way, the application may over or under charge some users depending on the consistency of the returned value. Worse, the theater would expect to make exactly $2000 on the last 100 tickets for each showing with the new pricing model, which may not be true with the new weaker read operation.

This example demonstrates that programmers need to be careful in their use of values returned from storage operations with weak consistency. Simply weakening the consistency of an operation may lead to unexpected consequences for the programmer (e.g., the theater does not sell as many tickets at the higher surge price as expected). If the application uses a counter value without error bounds, it may sell all 100 tickets at the lower normal pricing.

3. Type System

We propose a programming model for distributed data that uses types to control the consistency–performance trade-off. The *inconsistent, performance-bound, approximate* (IPA) type system helps developers trade consistency for performance in a disciplined manner. This section presents the IPA type system, including the available consistency policies and the semantics of operations performed under the policies. §4 will explain how the type system's guar-

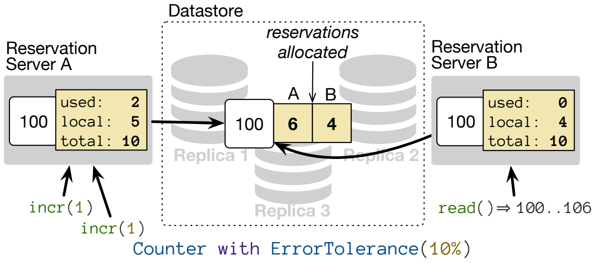


Figure 2. Reservations enforcing error bounds.

```
trait LatencyBound {
  // execute readOp with strongest consistency possible
  // within the latency bound
  def rush[T](bound: Duration,
              readOp: ConsistencyLevel => T): Rushed[T]
}
/* Generic reservaton pool, one per ADT instance.
   `max` recomputed as needed (e.g. for % error) */
class ReservationPool(max: () => Int) {
  def take(n: Int): Boolean // try to take tokens
  def sync(): Unit      // sync to regain used tokens
  def delta(): Int      // # possible ops outstanding
}
/* Counter with ErrorBound (simplified) */
class Counter(key: UUID) with ErrorTolerance {
  def error: Float // % tolerance (defined by instance)
  def maxDelta() = (cassandra.read(key) * error).toInt
  val pool = ReservationPool(maxDelta)

  def read(): Interval[Int] = {
    val v = cassandra.read(key)
    Interval(v - pool.delta, v + pool.delta)
  }
  def incr(n: Int): Unit =
    waitFor(pool.take(n)) { cassandra.incr(key, n) }
}
```

Figure 3. Some of the reusable components provided by IPA and an example implemention of a Counter.

Network Condition	**Latencies (ms)**		
Simulated	*Replica 1*	*Replica 2*	*Replica 3*
Uniform / High load	5	5	5
Slow replica	10	10	100
Geo-distributed (EC2)	1 ± 0.3	80 ± 10	200 ± 50
Actual	*Replica 1*	*Replica 2*	*Replica 3*
Local (same rack)	<1	<1	<1
Google Compute Engine	30 ± <1	100 ± <1	160 ± <1

Table 1. Network conditions for experiments: latency from client to each replicas, with standard deviation if high.

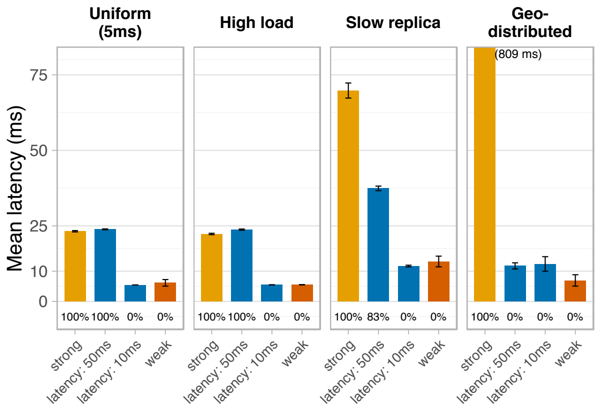


Figure 4. *Counter: latency bounds, mean latency*. Beneath each bar is the % of strong reads. Strong consistency is never possible for the 10ms bound, but 50ms bound achieves mostly strong, only resorting to weak when latency is high.

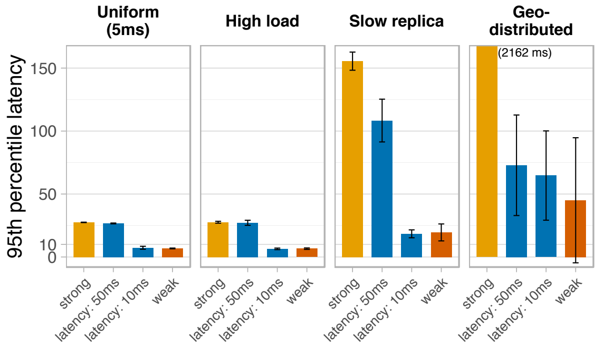
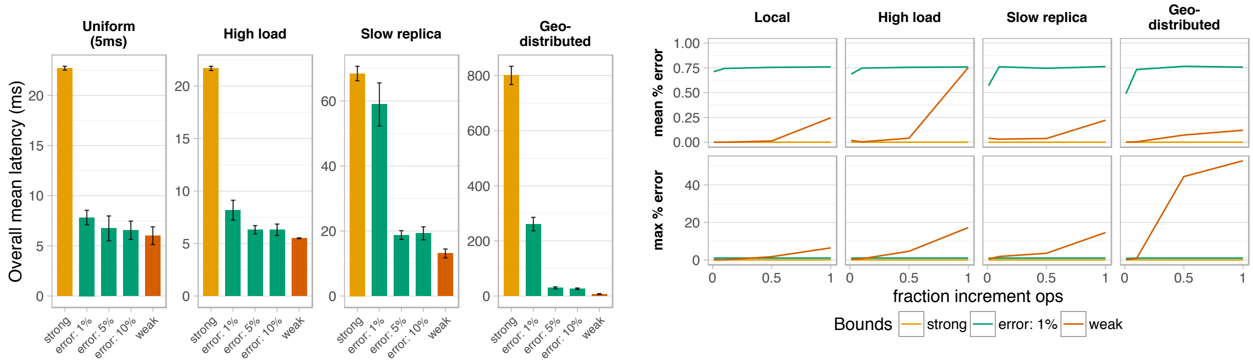


Figure 5. *Counter: 95th percentile latency*. Latency bounds keep tail latency down, backing off to weak when necessary.



(a) Mean latency (increment *and* read).

(b) Observed % error for weak and strong, compared with the actual interval widths returned for 1% error tolerance.

Figure 6. *Counter benchmark: error tolerance*. In (a), we see that wider error bounds reduce mean latency because fewer synchronizations are required, matching *weak* around 5-10%. In (b), we see actual error of *weak* compared with the actual interval for a 1% error bound with varying fraction of writes; average error is less than 1% but *maximum* error can be extremely high: up to 60%.

```
// creates a table of pools, so each event gets its own
// 5% error tolerance on `remaining` method, weak otherwise
val tickets = UUIDPool() with Consistency(Weak)
                  with Remaining(ErrorTolerance(0.05))

def purchaseTicket(event: UUID) = {
  // UUIDPool is safe even with weak consistency (CRDT)
  endorse(tickets(event).take()) match {
    case Some(ticket) =>
      // imprecise count returned due to error tolerance
      val count: Interval[Int] = tickets(event).remaining()
      // use maximum count possible to be fair
      val price = computePrice(count.max)
      display("Ticket reserved. Price: $" + price)
      prompt_for_payment_info(price)
    case None =>
      display("Sorry, all sold out.")
  }
}
```

Figure 7. *Ticket service* code demonstrating use of IPA types.

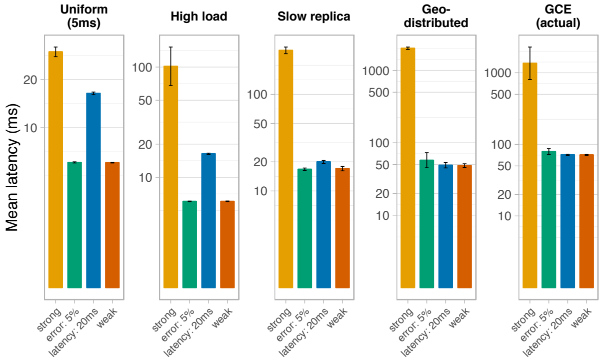


Figure 8. *Ticket service: mean latency*, ***log scale***. Strong consistency is far too expensive (>10× slower) except when load and latencies are low, but 5% error tolerance allows latency to be comparable to weak consistency. The 20ms latency-bound variant is either slower or defaults to weak, providing little benefit. Note: the ticket `Pool` is safe even when weakly consistent.

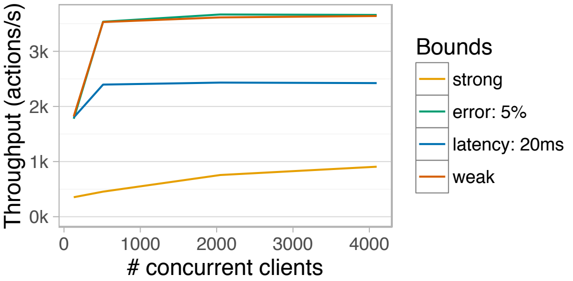


Figure 9. *Ticket service:* throughput on Google Compute Engine globally-distributed testbed. Note that this counts *actions* such as `tweet`, which can consist of multiple storage operations. Because error tolerance does mostly weak reads and writes, its performance tracks *weak*. Latency bounds reduce throughput due to issuing the same operation in parallel.

```
class User(id: UserID, name: String,
  followers: Set[UserID] with LatencyBound(20 ms),
  timeline: List[TweetID] with LatencyBound(20 ms))

class Tweet(id: TweetID, user: UserID, text: String,
  retweets: Set[UserID] with Size(ErrorTolerance(5%)))

def viewTimeline(user: User) = {
  // `range` returns `Rushed[List[TweetID]]`
  user.timeline.range(0,10) match { // use match to unpack
    case Consistent(tweets) =>
      for (tweetID <- tweets)
        displayTweet(tweetID)
    case Inconsistent(tweets) =>
      // tweets may not have fully propagated yet
      for (tweetID <- tweets)
        // guard load and retry if there's an error
        Try { displayTweet(tweetID) } retryOnError
  }
}

def displayTweet(id: TweetID, user: User) = {
  val rct: Interval[Int] = tweets(id).retweets.size()
  if (rct > 1000) // abbreviate large counts (e.g. "2k")
    display("${rct.min/1000}k retweets")
  else if (rct.min == rct.max) // count is precise!
    display("Exactly ${rct.min} retweets")
  //...
  // here, `contains` returns `Consistent[Boolean]`
  // so it is automatically coerced to a Boolean
  if (tweets(id).retweets.contains(user))
    disable_retweet_button()
}
```

Figure 10. Twitter application's data model with policy annotations, and code demonstrating how to use `Rushed[T]` to catch referential integrity violations and `Interval[T]` for approximate retweet counts.

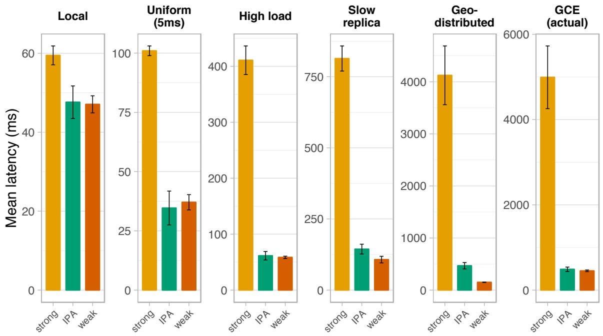


Figure 11. *Twitter clone: mean latency (all actions)*. The IPA version performance comparably with weak consistency in all but one case, while strong consistency is 2-10× slower.