Preprint

Disciplined Inconsistency

Double-blind submission

Abstract

To keep users happy and meet service level agreements, web services must respond quickly to requests and be highly available. In order to always meet these tight performance goals, despite network partitions or server failures, developers often must give up strong consistency and migrate to some form of eventual consistency. Making this switch can be error-prone because the guarantees of weaker consistency models are notoriously difficult to understand and test. Furthermore, introducing weak consistency to handle worst-case scenarios creates an ever-present risk of inconsistency even for the common case, when everything is running smoothly.

In this work, we propose a new programming model for distributed data that uses types to provide a *disciplined* way to trade off consistency for performance safely. Programmers specify their performance and correctness targets as constraints on abstract data types (ADTs). Meeting performance targets introduces uncertainty about values, which are represented by a new class of types called *inconsistent, performance-bound, approximate (IPA)* types. We demonstrate how this programming model can be implemented in Scala on top of an existing datastore, Cassandra, and show that it provides sufficient flexibility in terms of performance and correctness to handle a variety of adverse scenarios for applications including a shopping cart, Twitter clone, and ticket vendor.

1. Introduction

- Applications have performance requirements
  - Sometimes explicit in the form of SLAs, promising a certain latency or availability
  - Sometimes more implicit (i.e. every additional ms of latency reduces revenue)
- Constantly balancing performance vs correctness / programmability
  - If it isn't scaling well, or latencies are too high, then relax consistency in some places and hope…
- This is error prone: every time you change consistency, there are new reorderings and conditions to consider
  - new edge cases to handle, *implicit* in the consistency model
  - accidentally leak into places that weren't intended to be weakened
- Worse: conditions can change at any moment; node goes down, network unreliable, traffic surges
  - In test environment, inconsistency is typically unlikely
  - Adverse conditions in production can cause errors that never appeared in testing, or are very difficult to test for
  - No way to know if you've caught them all
- Furthermore, when conditions are good, there's no need to resort to weak consistency
- It would be great if we had a way to:
  - Express performance bounds
    - Have the system help achieve them
  - Make inconsistency explicit and restricted
    - handle different cases in a disciplined way
    - restrict possible values, and where they can be used
- So the question is: *where to introduce this abstraction?*
  - As part of the data type!
  - Couples the effects of mutating operations with reads
  - Concise and modular: re-use data types, no annotations on individual operations
  - Safe: inconsistency expressed as return types

2. Type System

- High-level goals
  - Explicit performance bounds (latency)
  - Explicit approximation bounds (error tolerance)
  - Results in IPA types which express the resulting uncertainty
- ADTs
  - can't just express these on the *read* side, most require knowing how the *write* was done
  - e.g. `Consistency = Read.Consistency + Write.Consistency`, so `Write.ALL + Read.ONE = Strong`, or `Write.QUORUM + Read.QUORUM`
  - Other benefits of annotating ADTs:
    - portable / reusable
    - modular
  - Similar to Indigo's ([@Indigo]) invariants, but expressing performance and approximation bounds
- Types of annotation
  - "static" bounds like `Consistency(Strong)` that fix a policy upfront
  - "dynamic" bounds like `LatencyBound(50 ms)` that choose a policy at invocation time

- per-method bounds for ADTs (e.g. `Set[ID]` has `size` and `contains?` methods that could have different bounds)

- Bounds
  - `Set[ID] with Consistency(Strong)`
  - `Set[ID] with LatencyBound(50 ms) -> contains(ID): Rushed[Boolean]`
  - `Counter with ErrorTolerance(5%) -> read(): Interval[Long]`
- IPA type lattice
  - Inconsistent (⊥)
  - `Rushed | Interval | Leased`
  - Consistent (⊤)
- Rushed
  - Consistency level achieved
- Interval
  - min, max, contains?, etc
  - linearizable within the error bound – as long as we stay within the bound, everything is strongly consistent
- Leased goes away
- Semantics of mixed consistency levels?
  - If every operation comes back strong, it's just like strong consistency was chosen in advance – so everything is linearizable
- Futures
  - (talk about how everything is implemented with futures, or just elide that?)
- All writes are statically at a certain consistency level
  - Why? So we don't have to reason about interactions with reads (would need flow analysis)

3. Implementation

We demonstrate one possible instantiation of the Disciplined Inconsistency model with an implementation of a Scala client, using Cassandra as the backing store. Most of the functionality required to implement the model is relatively datastore-agnostic; most Dynamo-style datastores support some form of tunable consistency, so porting our implementation to another backing datastore such as Riak should be possible.

[explain the basics of how Cassandra's consistency levels work] see: Cassandra Consistency

3.1. Latency bounds

As discussed earlier, a common desire is to be able to guarantee a certain response time, for example in order to meet an SLA. However, within that window of time, we would like to provide the strongest guarantees possible, so that users typically observe consistent, up-to-date data.

Conceptually, any Dynamo-style datastore implements configurable consistency levels by adjusting the number of replicas that a client request waits for a response from. [explain first how it would work conceptually by sending read requests to a quorum of replicas, and then proceeding with whatever we have when time is up; then explain how in Cassandra we have to cheat by issuing reads in parallel]

3.2. Reservations

In order to implement the `Interval` bounds, we build on the concept of *escrow* and *reservations* [10, 17–19].

We implement reservations as a middleware layer: a reservation server runs alongside each Cassandra server. Any operations with error tolerance bounds are routed to a reservation server, using the Cassandra client's knowledge of which replicas are up.

3.3. Leases

[???]

4. Evaluation

[explain how we simulate network conditions using `tc netem` and `docker` ?]

4.1. Microbenchmarks

- Latency bound
  - show how it can meet various latency bounds, compared with Strong and Weak
  - show that 95th percentile still meets latency bound!
  - show how many achieved stronger consistency, and how that correlates with actual consistency violations
- Reservations
  - show link between tighter bounds and lower performance
  - tie performance to the number of strong reads/reservation refreshes we had to do
  - show how interval width gets smaller with fewer writes

4.2. Applications

4.2.1. Shopping Cart

[demonstrate loading cart with a latency bound, but not allowing users to check out without doing a strong read]

4.2.2. TicketSleuth

[ticket sales app demonstrating hard lower bounds on counters]

4.2.3. Twitter clone

[demonstrating error tolerance for Counter (number of retweets), and latency bound for loading the timeline]

5. Related Work

5.1. Consistency Models

A vast number of consistency models have been proposed over the years. From Lamport's *sequential consistency* [13] and Herlihy's *linearizability* [12] on the strong side, to *eventual consistency* [25] 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. For example, a family of models including *read-your-writes* and *monotonic reads* use *sticky sessions* [23], which reduces availability in a small way, but provides users with a bit more certainty about what values they will observe.

A single global consistency model for an entire database or application is restrictive; some datastores support configuring consistency at a finer granularity: Cassandra [3] per operation, Riak [5] on an object or namespace granularity, as well as others [14, 22].

5.2. Explicit performance bounds

It is difficult for programmers to determine the correct consistency level for each operation. Ideally, everything would be as consistent as possible, but in some situations, performance needs (such as availability) force inconsistency.

[will probably have to introduce this earlier when explaining `Rushed`, but putting the text here for now] With *consistency-based SLAs* in Pileus [24], programmers can explicitly trade off consistency for latency. A consistency SLA specifies a target latency and a consistency level (e.g. 100 ms with read-my-writes). In this programming model, operations specify a set of desired SLAs, each associated with a *utility*. Using a prediction mechanism similar to PBS, Pileus attempts to determine which SLA to target to maximize utility, typically to achieve the best consistency possible within a certain latency.

In Pileus, SLAs are specified on each *read* operation, which returns both the value it got and the achieved consistency level. This allows programs to behave different depending on changing conditions. Our `Rushed` IPA types, which were inspired by Pileus, provide a more disciplined way to let programmers express how behavior should depend on consistency, protecting them from inadvertently misusing the returned value. In addition, Pileus's SLAs are assigned only to individual reads; writes are all assumed to be the same, and data type is not considered. Working with latency bounds at the ADT level allows reads and writes to be coupled, enabling more potential optimizations.

[are there other systems with explicit performance bounds enforced by the system?]

5.3. Controlling staleness

Most eventually consistent models provides no guarantees about how long it will take for updates to propagate. However, there are several techniques to help bound the staleness of reads.

Leases are an old technique that essentially gives reads an *expiration date*: the datastore promises not to modify the value that was just read until the lease term is over. First proposed to avoid explicit invalidations in distributed file system caches [11], leases have since been used in a multitude of ways: in Facebook's Memcache system [16] for invalidations, Google's Chubby [7] and Spanner [9] to adjust the frequency of heartbeat messages, and on mobile clients with exo-leases [21]. Warranties [15] are a generalization of leases, allowing arbitrary assertions over state or behavior. [explain how our leases relate (if they get implemented)]

[Probabilistically bounded staleness? (4)]

5.4. Types for distributed systems

Convergent (or *conflict-free*) *replicated data types* (CRDTs) [20] 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. For example, Set `add` and `remove` typically do not commute, but a CRDT called an OR-Set re-defines them so that `add` wins over `remove`, making them commute again. CRDTs can be enormously 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.

Bloom [1, 2, 8] is a language and runtime system for defining whole applications that are guaranteed to converge. Based around a conceptual monotonically growing set of facts, the language encourages coordination-free computation, but automatically creates synchronization points where necessary.

[Session types?]

5.5. Approximate types / Trading off correctness

- Cite some approximate computing papers
- Something something Uncertain‹T› [6]
- Conit-based Continuous Consistency Model [26]

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