Continuous Integration of Data Histories into Consistent Namespaces

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Abstract—We describe a policy-based approach to the scaling of shared data services, using a hierarchy of calibrated data pipelines to automate the continuous integration of data flows. While there is no unique solution to the problem of time order, we show how to use a fair interleaving to reproduce reliable ‘latest version’ semantics in a controlled way, by trading locality for temporal resolution. We thus establish an invariant global ordering from a spanning tree over all shards, with controlled scalability. This forms a versioned coordinate system (or versioned namespace) with consistent semantics and self-protecting rate-limited versioning, analogous to publish-subscribe addressing schemes for Content Delivery Network (CDN) or Name Data Networking (NDN) schemes.

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I. INTRODUCTION

The scaling and consistency of distributed information systems are two sides of an ongoing narrative in Computer Science about consistent and reliable access to data [1]–[3]. The two subjects go hand in hand, principally because increased scale means increased distribution over space and time, and thus greater uncertainty about when events occurred. Serial multiplexing is time-sharing, and shared memory policy is memory or storage space-sharing. Movement of data, physically and virtually, connects change over different forms of space and time through process trajectories [4]. Where such trajectories come together, they must be interleaved by defining a policy for their continuous integration [5].

Increased scale implies increased exposure to non-deterministic environmental influences, including the effects of faults, latencies, and contention for shared memory (races). Processes, which attempt to assimilate and calibrate data from multiple sources into a singular consistent view for all, struggle against the limitations of communication and scale. The semantics of this assimilation are typically left undefined in literature, as if obvious and universal, but aggregation is a form of data pipelining and there are several alternatives. This is where we shall try to do better.

A number of familiar tools are in widespread use, for defining and ensuring data consistency, and after fifty years there’s an understandably large literature on the topic, see for example [1], [6]–[12]. A common philosophy is to try to conceal the side-effects of scale behind infrastructure, which simulates a single computer by brute force, but this is both expensive and increasingly problematic in the age of carbon budgets and energy awareness [13]. Often these involve a high cost in terms of communication and memory; however, they do not scale favourably to either the very large or the very small.

A key part of the difficulty is designing a scalable data recorder lies in determining the relative order of events that happen within independent processes, sourced from different locations and integrating them into a common history (scaling causality itself). Events without causal dependencies have no natural order, and—while we might try to define one by means of a global clock—a clock only has meaning within a limited scope, where the time it takes to read the clock is insignificant compared to the ratio of change of the processes themselves. At current process speeds, that assumption fails quickly in a globalized world.

Another part of the difficulty in scaling has to do with the insistence on ‘push-based’ update models for the imposition of data transactions. It’s hard to overstate how deeply ingrained this thinking is in IT. Push methods rely on purely reactive methods, which are designed on the implicit assumption of a sender update process that’s sparse compared to the available schedule of the receiver. For saturated update streams, the data pipelines favour a scheduled ‘pull’ processing model, which optimizes the scarce time resource at the receiving end, and avoids the unnecessary contention of ‘push’ semantics [14]. The interplay between the dynamic and semantic issues then has to be balanced: how should we dimension and interpret the intended behaviour of a system? These are not questions that can be answered once and for all cases, so there is a tendency to succumb to ad hoc approaches. Such ad hoc solutions lead to uncertainties and reliability issues.

The challenge faced by any data service is to present a consistent view of updates, and historical timelines to all users, regardless of where they might be located. This issue can only be solved by curating a solution, since there is no absolute notion of time that applies to all agents within a distributed system. Thus, several different solutions may be possible, and different solutions may be more suitable for some clients than for others.

By now the infamous ‘CAP conjecture’ dominates many popular discussions about such consistency of access to data. The CAP is the poster-child for how ambiguity arises due to incomplete semantics [15]. In practice, it’s impossible to give meaning to a single unique view of data for all clients. All such attempts at consistency involve some kind of compromise to manipulate space and time, either by imposing a wait, a limit on observability, or by accepting variance in data arrival times to different client. One variance that’s frowned upon is differences in the perceived order of events, and we take it as an axiom that preserving the intended order of data is a basic promise that databases must keep. We resolve this issue by defining an adaptive scale-dependent tradeoff—a kind of data prism—in which data flows are ‘lensed’ into a focused beam of updates, by fair weighted interleaving.

Lamport was early in recognizing the issue of process relativity, by defining a notion of consistency for distributed information [16]. He used this to build Paxos, a widely adopted quorum solver—for determining outcomes according to a fixed policy [6]. It builds on Gray et al’s two-phase commit protocol [17]. Since agreement is the basis of semantics in any collection of processes, it’s natural that this problem would dominate concerns about distributed intent. However, the quorum problem is about semantics of agreement, and is distinct from the purely dynamical problem of observing data consistently. The vector clock approach Fridge [18] identifies similar issues. The ability to be certain of outcomes by asynchronous messaging is subject to the so-called FLP no-go theorem [19]. The notion of rigid entanglement allows us to side step this by maintaining synchronous communication [20] for part of the process.

II. OVERVIEW

In this note, we describe a generic spacetime approach to resolving the order and causal consistency of data, applied to storage, processing, replication, and retrieval [2], [3]. Unlike quorum solvers, which define correctness by vote, our definition of correct version is based on deterministic version numbering, and causal interleaving policy. Data remain in place at their point of collection and a hierarchy of associative ‘index’ pointers is generated in real time to assign coordinates to consistent slices of data. These become observable globally after a scale-dependent delay. We describe the dynamical process

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1 The distinction is analogous to that between Ethernet and ATM or MPLS, in networking, for instance.

2 The conjecture was misrepresented as the CAP Theorem, though no proper theorem has ever been expressed to cover the claims. The statement of the claim has gradually changed over time to try to transform it into a provable theorem. However, it’s value lies in the rough observation of a truism rather than in a provable statement.
by which addressable namespace coordinates are assigned to changes, in order to integrate data both dynamically and semantically into past and future ‘cones’. This is a shared view, for all clients, based on a fair interleaving of random spacetime arrivals (see figure 2).

An important side effect of this approach is the impact it has on cache replication. Replication can be decoupled from other processes to maximize availability and the minimize the impact of partitions. The replication of multi-version state can be acquired from an authoritative source, by means of a change log. This is a standard approach used by journaling filesystems and for rewinding database snapshots. The more difficult problem occurs when we want to replicate state from multiple sources, and at different locations, in order to a reconstruct a consistent remote cache. This is where we apply the concept of a distributed clock to construct a ‘Just In Time’ partial cache image that preserves the semantics of the clock. The proposed clock therefore preserves a notion of the original processes as possible. Finally, we comment on the tradeoffs of the network (writes), to publication of change (commits), the entire data pipeline: from change capture at the edge replication and caching on demand.

Our proposed solution is based on ‘proper time’ counting (the root concept behind tensor clocks [21], [22]), and can be scaled from very small to very large assemblies of collaborating agents. The dynamical trade-offs can be controlled deterministically by exploiting a hierarchical semantic coordinate system [2], [23], and so-called ‘once only’ semantics of updates can be handled (in the usual manner) by designing for convergent (idempotent) name coordinates [24]. The automatic assignment of versions to key values is thus basically in the spirit of ‘Continuous Integration’ (well known from Software Engineering), and is somewhat similar in spirit to addressability for Name Data Networking [25], [26] or Content Delivery Network publisher-subscriber schemes.

The plan for the paper is as follows. We begin by looking at a causal collision-resolution mechanism for overlapping transactions involving a single key-value. This acts as a reference and point of departure. Then we proceed to scale this process, in spacetime, by decoupling the processes within the entire data pipeline: from change capture at the edge of the network (writes), to publication of change (commits), subscription to data channels (versioned reads), and finally replication and caching on demand.

The observability of committed changes as publish-subscribe channels (sometimes called ‘liveness’ of updates), is integrated into a shared absolute coordinate system, by a process of statistical interleaving, which defines a consistent and intuitive view of the past. We infer that this may be defined to be as close to what was intended by the original wrig processes as possible. Finally, we comment on the tradeoffs of our approach, specifically the maximum rate at which data can become observable by the whole hierarchy and the implications of this for distributed computations.

Our analysis in this note is based on Promise Theory [14], [27] and its derived model of Semantic Spacetime [23] (see the appendix for a summary of definitions and notations). The components of our model are all known (at least in principle) in the literature, and we hope to clarify their composition into a distributed collaboration to distill a generic solution.

III. DATA CONFIGURATION SPACE AND BACKGROUND

Data storage management is essentially a form of rapid incremental configuration management on demand. The scope of data management is usually much greater than one would normally expect for ‘configuration’ changes (a term usually associated with more slowly varying permanent infrastructure). By now, the accepted approach for configuration is to ensure an invariant state through monotonic and idempotent state convergence, as proven by Burgess in [24], [28], building on Shannon’s error correction theorem [29]. Convergent correctness in a data store may be viewed as a version of error correction over a single policy domain. Meanwhile, contention-free handling of shared memory was resolved for distributed version control systems using a ‘Many Worlds’ scope (see for example [30] for a review). The essence of these approaches is now part of distributed resource schedulers like Kubernetes [31] and message relays like Kafka [32]. We apply the same reasoning to construct an invariant but versioned history over distributed changes for a more dynamic data service, i.e. a generalized database, with contention free semantics. We have to solve the spacetime coordination issue, and select unique key names for idempotently promised values. We begin by defining the agents of the system and their high-level promises.

Figure 1 shows the hierarchy of software or hardware agents we refer to for the clock. We distinguish three roles for agents: handler agents $A_i$, the parent handlers that aggregation handlers as children $P_j$, and the root node(s) $R$. There may be several levels of parent handlers before converging onto a master parent or root node.

The principal agents we shall refer to in our discussion for a hierarchy according to their functional roles. We define them and their group labels in this table:

| Agent | Role       | Cycles Group       |
|-------|------------|--------------------|
| $A_i$ | Handler    | $G_i^{(n)}$        |
| $P_j$ | Parent     | $G_j^{(n+1)}(A)$   |
| $R_k$ | Root       |                    |

The arrangement of their roles is depicted in the figure 1. This differs slightly in detail from the idea in [2]. Note in particular how spacetime is covered by a spanning tree composed from cells, each of which contain cyclic ‘ring’ structures.

The basic agent $A_i$ could be associated with a server process running on a computer, but this association is increasingly speculative given the many layers of virtualization involved. The $A_i$ form collaborative groups, whose roles are elaborated below. Notably, the members of a group form a ring which becomes a tool for interleaving activity within the clock. These groups a joined together by parent groups, also formed from basic agents like $A_i$ but we call these $P_j$ for clarity, with a different role to play. The parents, in turn, are joined together by parents of parents, and so forth.

To avoid an excess of notation, we only refer to a single bundle of threads from agents $A_i$ in a single cell, via a single parent, up to a single root node. $G$ refers to a single cell or group of handlers $A_i$ with a common parent $P$ in what follows.

The basic role of the $A_i$ is to be an independent transaction processor, with its own private storage. We can think of these
Fig. 1: The arrangement of agents in the configuration of a hierarchical service. The arrangement forms an implicit clock that computes the past cone of autonomous agents at different scales. The \( A_i \) receive client requests independently. Local requests can be completed independently; requests involving other shards may involve delegation. Committing of data is handled by parents and made public once accepted. Each local clock for \( A_i \) is independent and unsynchronized, but if a search references data from other agents, then any agent can find out which versions belong in its past cone by consulting the hierarchy of parents as an index.

as shards with transparent replication for redundancy, but a very similar configuration could also be used for replication using the same clock approach. The latter would be similar to the use of an entanglement approach [20]. This means the role of a group \( G(A) \) formed from the \( A_i \) is as a database for ‘local concerns’. The precise meaning of this is ambiguous in a networked world. The basic role of the parent nodes is to be a single point of calibration for the clocks of independent groups \( G(A) \). The same applies across the subsequent levels by induction.

IV. Design Promises

A. Strategy overview: a global data pipeline and clock

Before turning to details, let’s summarize the promises our hypothetical distributed data service would be expected to keep:

1) Service handlers promise to accept client transactions that involve storing and retrieving versioned data histories, destined for one or more data subscription channels, each with different policy-defined semantics (suitable for different applications). The default channel always shows data service snapshots with ‘latest official version’ semantics, for all key-value pairs \((k,v)\).

2) Each channel promises a consistent ordered sequence of versions, forming a causal history of earlier written \((k,v)\) data.

3) Each handler promises to expose client read-queries only to data values that are fully resolved and invariant, from the past time cone the query concerned (see figure 2).

4) The total system promises to capture and preserve the intended total order of all serially executed changes to a given key-value stream by a given client, and to define the partial order of all causally unrelated (parallel) queries, according to a fair policy of interleaving.

A rough schematic of the algorithm is as follows:

- When any command or transactional procedure is started, the cone of absolute past for the process is determined from the global clock infrastructure. This defines what shared values the process can employ for its computation.

- Once a transaction procedure is running, it may accumulate temporary writes. Temporary writes, such as those used in the calculation of sums and composites etc, will never be seen by any other process.

- All writes, whether intended to be permanent or not, are written immediately to the private workspace belonging to the transaction, in the manner of private local variables. These are never ‘committed’ or published.

- In order for written data to become permanent new versions of \((k,v)\), i.e. invariants of the service, a winning representative must be selected from possibly any competing contenders, and be authorized by adding
Agent changes are clearly fluid and changes are continuous, so this distributed data pipeline actually forms a ‘global clock’ (version control parlance). A scaled up and down. The main method at our disposal, for data (on a human scale) can be maintained as services are to ensure that all the promises and meanings we intuit about the likelihood of agents seeing precisely the same information is part of a single shared process (i.e. in the same branch, in this is deterministically possible, so that every agent is that this is deterministically possible, so that every key-value pair in past key-value pairs (retarded boundary conditions). The future of possible states generated by the ‘now’ point depends only on values from the past cone, not from anywhere outside. Deferred outcome processes may depend on future events implicitly (advanced boundary conditions). When these overlap, we need to use process context to disambiguate semantics.

Fig. 2: The meaning of space and time in a data system: time is change, and space is independent context (memory or state). The past and future cones that define the spacetime of each process. The past refers to data already archived immutably in the proper timeline of a process. Transactions at the meeting point can only depend on past key-value pairs (retarded boundary conditions). The future of possible states generated by the ‘now’ point depends only on values from the past cone, not from anywhere outside. Deferred outcome processes may depend on future events implicitly (advanced boundary conditions). When these overlap, we need to use process context to disambiguate semantics.

This distributed data pipeline actually forms a ‘global clock’ to batch data into a coarse grained partial order, by virtue of its policy for interleaving authorized ‘commits’ from all cells. [2], [5]. The result of this schematic process is to curate a set of consistent channels (including the default ‘latest version’ view). The handling agents $A_i$ promise to ensure that no two processes are ever allowed to ‘commit’ a write to the same key in the same global time slot; however, alternatives and race losers could remain in semantically separate channels.

A key promise for data subscription replicas is that all agents at the same spacetime coordinates will see the same past data cone. We need to define sameness:

**Definition 1 (Sameness of snapshots):** Two snapshots may be called equivalent (or ‘the same’) if every key-value pair in their past cones is identical. This occurs if the two snapshots are computed from the same global time coordinate (on the hierarchical clock).

Agent changes are clearly fluid and changes are continuous, so the likelihood of agents seeing precisely the same information for very long is small if changes are frequent. The key point is that this is deterministically possible, so that every agent is part of a single shared process (i.e. in the same branch, in version control parlance).

**B. Locality as a design principle for correctness**

The challenge of scaling data is usually presented as the ability to cope with a large amount of it. The harder problem is to ensure that all the promises and meanings we intuit about data (on a human scale) can be maintained as services are scaled up and down. The main method at our disposal, for preserving these semantics, is to trade the ability to see change for greater dependability.

**Definition 2 (Service correctness):** Correctness of a service is defined to be the state in which explicit promises have been given for the service, in each distinguishable context, and where these are kept for all observable outcomes.

Delaying the observability of data affects the ‘liveness’ that we can promise about changes, so we need to ensure low latency responses on a number of levels. Writes can be effectively immediate (lock free), but the visibility of the changes for others will depend on several factors. An equitable solution, with easily understood semantics is to use locality as a principle (i.e. what we experience about ourselves is local and familiar; what others experience far away is less visible and less relevant to us). When we need to read data, the larger the spacetime region involved in collating the data, the greater the range of uncertainty in its liveness, partly due to the time it takes to retrieve the past cone for a transaction, and partly due to the time it takes to integrate changes to the cone into the coordinate system, as new data are written.

**Locality** is the principle by which the observation and capture of changes are kept as close to the point of interaction as possible for speed and accuracy. Other issues, like energy conservation are also benefitted by local thinking. Data searches, however, span data that are distributed over multiple shards and possibly stored over a wide area. Locality is particularly important for calibrating changes (writes) accurately in time, since a single point of change makes a single version semantics straightforward. For read-only interactions, locality is not as much of an issue as long as records are proper invariants (sometimes called immutable values) of spacetime processes. However, variations in version over spaced caches is a familiar problem where data are shared and dynamic.

Traditionally, one applies push-based thinking to build services. There we control the ability to expose or limit access to resources using mutual exclusion (e.g. mutex locks). These serialize access for critical sections and impose a local order, which is familiar, but costly in terms of delays and busy waiting. Version control schemes for parallel workflow, and Content Free Replication Types (CRDTs), handle this using private branches. We can combine branches for wait-free pipelining with restricted observability for avoiding contention. This is analogous to ‘look ahead’ and deferred publication³. Once data are invariant and uniquely referencable, published data can be replicated any number of times, and temporary caches can be brought arbitrarily close to clients for efficiency using some state replication policy [33], [34].

Locality is closely associated with centralization (see figure 3), i.e. the use of a single point of change—though the latter is often represented as a controlling concept rather than a calibration issue. The main functional meaning of such localized centralization is to create single-valued outcome, by using a single process for calibration [14]. The Downstream Principle in Promise Theory [14] implies that time calibration (and ordering) is arbitrated locally. So, the strategy for ensuring consistency would be to localize all shards of shared data to a small area.

³Deferred observability leads to change phenomena analogous to non-local quantum probabilities, presumably for the same reason: observation is decoupled from the processes that marshall the configuration of resources.
We can eliminate input/output bottlenecks, but only at the cost of a delay in the availability of consistent information (extra latency in computing parlance). Pragmatically, we need to design a pipeline to publish data changes using a single-valued coordinate system, based on past, present, and future.

V. Causality

At every location throughout a system, causal changes originate from the interface between handlers and clients (what we call the ‘edge’ of the system). We expect an intended change to be reflected in what we see from that moment forwards. We expect what we already know to be dependable, subject to some possible interference by competing clients. Our local region is where causal ‘intent’ is sourced from, and thus we consider this to be the origin of meaning for data—close to the context in which changes arose. Locality thus tells us there are two issues in resolving this problem:

- Resolving intentional order for versions of \((k, v)\) at each handler location \(A_i(k)\), and
- Curating a cooperative non-local interpretation, i.e. one that spans a broad reservoir of data that spans a wide area of spacetime.

These are the challenges we describe next, by designing a pipeline for spatial integration with temporal flow. On a theoretical level, this involves some deep issues about the exchange of interior and exterior time, by redrawing boundaries between public and private scope, when scaling [4], [35]. Naturally, there is no free lunch when it comes to consistency. We can eliminate input/output bottlenecks, but only at the cost of a delay in the availability of consistent information (extra latency in computing parlance). Pragmatically, we need to design a pipeline to publish data changes using a single-valued coordinate system, based on past, present, and future.

A part of causality, which is not often included in academic presentations, is context. The purpose of data updates may be of significant importance to the behaviour of a service. This is one reason why we need so many different kinds of database for different applications. The differences are particularly noticeable in replication of state. For example:

- When incrementing a counter or balance between many clients (coordination). The value corresponding to a primary key is being overwritten continuously and there is a ‘current’ or ‘latest’ value.
- When collecting a data lake or warehouse. Data are cached and never or rarely overwritten.
- When writing a timeseries, journal, or log. Data are appended but never overwritten.

VI. Continuous Integration Coordinate System

In this section we detail the semantics and dynamics of the spacetime coordinate system used to label committed data. We understand data processing ‘transactions’ to be extended procedural threads, not merely single read or write events. We assume that a client \(C_a\) is the broker responsible for managing a transaction. It must therefore have access to the time counters of the hierarchy. We shall not discuss possible implementations of these agents.

A transaction may read many records from anywhere in the dataverse, combine them, and write a single result or update every record one by one. Such large scale operations lead to extended contention, which interferes with other operations. These explosive cascading changes are hard to understand, for humans, as we tend to think in terms of our own narrow field and perception of time. Time consistency is built around the concept of single cause leads to single response (1:1 causation, see figure 3), so it would be advantageous if technology treated every such transaction as if it were an instantaneous operation too. We can manufacture this illusion by restricting observability, in the same way that human experience is limited.

A. Localization of commands and transactions

Consider a number of clients \(C_a\) interacting with a stateful software service—a database—through a number of parallel handlers \(A_i\) (see figure 4). Each stream of changes from a clients \(C_a\) to a handler \(A_i\) forms a converging data pipeline, with possible contention around changing a notion of ‘current value’ (see figure 4). Each interaction thread between \(C_a\) and a single state location \((k, v)\) at \(A_i\) forms its own proper time history unless they collide with one another at a particular location \((k, v)\) during the same causally dependent interval.

Since the key names are shared between all the competing threads, indiscriminate updates will then interfere destructively with one another unless we intervene to keep them apart. Without defining explicit semantics for a resolution, this would lead to an unclear outcome. Whose intended change wins this race? The underlying problem with this view is that the concept of ‘current value’ is neither an invariant nor uniquely definable property of a distributed system: it’s an illusion of a single observer’s timeline. Different clients understand ‘here and now’ differently from others. The curator of a shared outcome has only two main options for taking what was stacked in parallel and mapping it into a serial stream by multiplexing space and time:

- **Time separation**: Agents race and coordinate individually to overwrite the latest version of a key-value pair. Coordination must be maintained between the agents using some form of interprocess semaphores.
or mutex locks. All possible futures ‘collapse’ into a single shared version of global state. In case of contention, ‘rollback’ of the shared state may be required to maintain the illusion of correctness for a single timeline; however, the fact that there is an interference of more than one agent’s intent makes rollback of client state impossible (non single-valued), so attempting rollback is fundamentally ambiguous for clients (see [36] for a discussion in relation to division by zero).

- **Space separation.** Alternatively, each agent works in separate private branches of the data namespace they wish to change (as in distributed version control [30]). Coordination is unnecessary, because the branches do not interact except through a shared past. This is the ‘Many Worlds’ version of global state. It’s well known in programming as the local private variable approach. Future merging of these separate branches into a permanent shared result is a policy-based decision and requires additional work (no free lunch). The receiver is free to curate any combination of changes, or even invent something totally new, in principle [5]. Rollback is never needed in this approach as every change can be considered intentional. Unused branches can be garbage collected after a certain horizon to avoid an exponential explosion of state.

We adopt this latter approach, where the correctness of a merger is an ad hoc decision for the receiver of the two branches, and we look for a resolution that’s equitable in a general setting.

It’s important to realize that the original client sources of the data have no access or ‘right’ to resolve conflicts downstream after they have handed over data to the receiver. Moreover, the perceived order in which changes are made across different branches is not necessarily a relevant criterion for choosing alternative outcomes, since it’s only observable by the receiver as a single point of calibration [27]. We compromise between these methods to curate a fair process of interleaving, performed in ‘real time’. This approach is sometimes known as Continuous Integration in software engineering.

**Remark 1 (Data pipelines):** Data pipelines have a exactly analogous problem to solve: data from multiple sources, e.g. different sensors, arrive at some aggregator process and have to be combined (say into a statistical overview), Coordination is needed to decide which sampling timeframe data belong to. The receiver is the only agent capable of deciding this to create single-valued result. Policies for integration were described in [5].

**B. Scoping of program variables for data transactions**

The declarative aspect of data query languages presents a scoping challenge. Functional and imperative programming languages solve the problem of transactional integrity for procedures using private local copies of data to build ‘pure functions’. Inputs are copied into local memory by value and the function then works on the copy, leaving the original immutable. Several functions can operate on their own copies independently, without interference. Databases have yet to fully take such methods on board, though snapshot isolation is a partial adoption of the idea [37]–[39], and CRDTs are the natural correspondence [9]. We apply this idea to the formation of channels for named data distribution.

**Definition 3 (Private proper time or version):** Let \((k, v)\) be a key-value pair owned by a handler \(A_i\). A private proper time increment or version or version of \(v\) (which we denote \(v_n\) for version \(n\), where \(n\) increments with \(t(A(k))\)), is promised by the handler thread at \(A_i\) on the arrival of any new transaction, for any \((k, v)\) accepted by \(A_i\) from any client.

We need to publish an outcome, from a single winning update, in a sequence at each point \(A_i(k)\), at the moment changes are made public, thus:

**Definition 4 (Public (shared) proper time or version):**

Let \((k, v)\) be a key-value pair owned by a handler \(A_i\). A public proper time increment or version or version of \(v\) is promised to occur on committing the outcome of a winning transaction for all \((k, v)\) altered by the unique client thread. A public version number has the role of a timestamp, determined by the top root note \(t(R)\).

Notice how the decision to see and accept an external write command is an autonomous decision of the handler \(A_i(k)\). This makes the definition of any policy a promise that only \(A_i(k)\) can make, for each \(k\).

**C. Proper time simultaneity**

We can now define the meaning of ‘at the same time’ with respect to proper time. This is different for reading, writing, and committing. Note that a client \(C_k\), which brokers connections with key handlers, is different from a key handler \(A_i\), which is only responsible for writes (and perhaps reads) for its custodial keys.

**Definition 5 (Simultaneity of reads and writes):** Read and write operations are interior to their parent transactions. If the coarse (exterior) time counter to two operations is equal in any counter component of the tuple \(t(A), t(P), t(R)\), then they are simultaneously over the scale represented by the tuple component.

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2 The Datomic database, for example, has drawn this comparison with the immutability of past events. Hickey [40], [41] has popularized this in talks, though the formal details do not seem to have been published.
Scaling this to extended collections, we have:

**Definition 6 (Simultaneity of commits):** Two committed values are said to be locally simultaneous if their outcomes are accepted by a parent in the same time interval tuple, \((t(P), t(R))\).

In practice, this means that we consider data values that belong to the same proper time ‘snapshot’ to be simultaneous. The subtlety lies in the fact a snapshot of smaller spatial reach can be resolved more accurately (with finer granularity) than a larger one.

We state now a principle of minimal scope, which is central to resolving a global notion of consistent state:

**Principle 2 (Minimal scope published by ‘commit’):** All pairs \((k, v)\) written by an agent \(A_i\) are made as interior promises, whose outcomes are unobservable by exterior agents (clients, etc), until a decision is made to publish the result on the exterior to become part of a shared past cone. Only exterior times are observable by client transactions.

The implication of these definitions is that the ‘commit’ operation, for a database, is the decision to propagate the outcome (of a write) up the hierarchy to the root node, adding to the observable values of a subscribable channel.

**D. Semantics of the client interface**

We begin at the edge of the system, where several clients \(C_a\) (i.e. the sources of data and work) contend for access to a single key \(k\). We’ll assume the client itself is the broker for working with multiple shards. A client can find a shard handler’s address via a directory service (analogous to DNS for the database), which is an invariant since the location of a key does not change. Thus, all requests to read or write \(k\) converge on a single data handler agent \(A_i\), whose task it is to accept and record changes in the form of key-value pairs \((k, v)\):

\[
C_a \xrightarrow{+O} A_i,
\]

where \(O\) is an operation (private read or write). The reading of a known data value version may go to its custodial handler \(A_i(k)\), or to any read-only cache or replica.

In the language of Promise Theory, interactions with the handler begin with clients \(C_a\) imposing some command (+), resulting in a transaction \(T_x\), onto the service handler \(A_i(k)\). This interface defines the edge of the system, with \(A_i\) on its interior and \(C_a\) on its exterior. In general, the index \(a = 1, 2, \ldots\) may run over many different clients, and the index \(i = 1, 2, \ldots\) will run over many different handlers. In order for a response to be triggered, the handling agent has to accept some or all of these transactions

\[
A_i \xrightarrow{-O'} C_a,
\]

and the accepted (-) portion is \(O \cap O'\). This allows for access controls and privilege levels, as well as throttling of commands from clients.

Interactions or transactions between clients and handlers are not necessarily point-events. They can last for extended intervals, involve many reads and writes, and thus span data that are distributed across a wide area of system (in space or time). The control structures for this lie with the client. The convergence of more than one client onto a single handler (see figure 4) may therefore involve significant contention for the same resources, especially for long running transactions.

The handler multiplexes parallel threads and thus entangles clients’ outcomes together. Where client dependencies overlap, this leads to a ‘race’ to acquire exclusive rights to change states \((k, v)\). The handler has to resolve these races fairly and quickly to ensure that the data service keeps its promise of being a single-valued function of \(k\) for all future interactions, as well as a timely reflection of current events—this is the mathematical expression of what’s expressed as data consistency in the technology literature.

**E. Client race adjudication and policy semantics**

Resolving the outcome of races to change a single key involves the following criteria:

1) The ability to retain and separate past \((k, v)\) values, i.e. data histories, whose values have already been determined in the immutable past, from values that are in dispute in the present or the future. We call this the determination of the past data cone (see figure 2).

2) The ability to identify collisions (sooner rather than later) when the evaluation of commands or transactions will contend for certain keys. This may be predictable from the semantics of the command, but—in the worst case—processes may have to play out until the last moment of a collision in order to determine which keys will be affected. If the process is long, cancellation of a particular client’s transaction may involve a significant waste of time, energy, and other resources.

The semantics of resolving races may impact data flow significantly. A millisecond difference in latency could be the difference between a detectable collision or none.

- Should we insist that all but one of a set of parallel transactions fail in case of a collision?
- Should changes be queued with a definite order?
- Is it right to allow a value, which was just written, to be overwritten by another process just because it narrowly avoided collision? Should key-value pairs have dead times, as neurons do to prevent thrashing?

These questions are rarely asked of services, but they express particularly relevant aspects of intentional client behaviour. Was a particular update a characterization of the moment, whose relevance was temporary, so that a single failure could be dropped (unreliable delivery)? Alternatively, was it a critical step in balancing some account of a broader process whose loss could have enormous impact? Such characterizations have to be embodied by a policy for resolving missed opportunities to write data.

Simple policies for selecting a winning transaction are well known from scheduling, e.g. First Come First Served (FCFS),

\[\text{In general, handlers might alternatively pull data from known sources by a regular schedule, e.g. when replicating data for backup, etc, but one normally thinks of data arrivals as randomly imposed events.}\]
Shortest Job First (SJF), etc. The mode of resolution could depend on the visibility of the outcome: will the result of a write be shared between all future clients, or will it be private for certain groups? Groups can separate flows into ‘channels’, implying a policy for the eventual channel a transaction will end up in, i.e. will transactions collide or be placed in separate branches?

F. Policy for resolving write collisions

Consider then how parallel changes are handled when contending to change a single key. Collisions between clients occur when at least one of a number of simultaneous transactions attempts to write the same keys that are being read or written by others in parallel.

No interior writes are visible outside the transaction, for its duration. Commit operations are all registered at the end, as exterior time \( \tau \), i.e. at the close of a transaction (regardless of when they were written in interior time). Concerning the interior time, if a value has been read at \( t_2(1(A(k))) \) by \( T_1 \) and it is written later at \( t_2(A(k)) \) by \( T_2 \) then there is a collision and we need a policy to resolve. If the policy is FCFS:

- \( T_2 \) will never see \( T_1 \)'s changes, since they lie in its future cone. So \( T_2 \) cannot perform any reads or writes, to a key affected by \( T_1 \), until after \( T_1 \) has committed. Increments must remain relative until the moment of committing (i.e. the values should not be based on an earlier read).

- If \( T_1 \) and \( T_2 \) both read and write the same key, e.g. both increment or decrement, then \( T_2 \) must be rejected by the handler, because we know that the value it sees is going to be invalid by the time it might commit its own changes.

We point out that the contextual semantics of the use-case is important here. When the transactions involve relative updates, they have to read the previous version in order to compute the new version to write, so overlaps are potentially complex constructions. As mentioned above, we won’t discuss the implementation of these promises, which are challenging.

One could try to make the algorithm perform some complex traffic management, but this could lead to presumptuous behaviour. We have to question why two agents would be allowed to alter data simultaneously in the first place. This is a question to be resolved by the imposers of intent. Promise Theory tells us that impositions can’t be resolved by the receiver, and are therefore likely ineffective in generating their intended outcome. Some out-of-band communication between clients is thus likely required to find the ‘correct’ resolution to this contention. A simple failure of an overlapping transaction may delay a client, but is a neutral resolution.

With this meta-policy, there are only two kinds of collisions to handle, which correspond to ± promises in the data interactions:

- **Collisions of intent (+,write).** One or more client transactions attempt to claim the same version \((k, v)\), by writing to it in the same proper time interval.

- **Collisions of dependency (-,read).** A client intends to write \((k, v)\) and other parallel processes depend on the value of \((k, v)\) for their own outcome.

**Proposition 1 (Read conflicts):** Reads can be avoided by promising no observability or inclusion of data values committed at or after the moment at which a transaction began, in a later version.

In other words, transactions may only be granted access to read from the past cone in a transaction evaluation (see figure 2).

The selection of which version from the past to read remains the responsibility of clients \( C_n \), by the downstream principle. The common and natural choice is to read latest version at the ‘top’, ‘end*, or ‘head’ of the chain of values \((k, v_n)\) where \( n \leq n \).

**Proof of absence of read conflicts:** If all changes to data are assigned a greater version number in each channel, both privately and publicly, then there can be no version overlap between \( r(v(c)) \) and \( w(v'(c)) \), provided

\[
A_i \xrightarrow{v'(c) > v(c)} C_{a_j}
\]

which is a promise of the handler.

These policies thus resolve the promise to avoid read conflicts—a promise rather than a guarantee, because it assumes the handler agent keeps its promise. The presence of bugs or other flaws can still undermine this.

![Fig. 5: Transaction race resolution is performed at the edge, by authoritative key handler agents \( A_i \). Clients, from any geo-location, initiate processes in a data handler, which may handle multiple sessions in parallel. A handler assigned to a client process will only read from the past cone measured from the starting time of the request. Any changes to values are written ‘immediately’ by handlers into private workspace, and the final publishable set of changes is committed in a single clock-tick at the end of the transaction as its final act (shown as dark squares). Overlapping processes race one another relative to the final channel curator process. The channel curator keeps time by a hierarchical distributed clock, and accepts convergently named slot-reservations for a single key/channel on a FCFS basis, and places them into a timeslot within its publication schedule from its current future cone.](image-url)
We can thus turn to writes (see figure 5):

**Proposition 2 (Write conflicts):** Write conflicts can be avoided by: (i) immediately and serially performing writes to a namespace which is private to the transaction, and (ii) selecting only one winning client from the list of clients that would commit (publish) their changes in the same time interval.

The freedom to pursue variants of this lies in the ability to curate different channels from the stream of accepted temporal values. We define the default policy by

**Definition 7 (Default collision policy (FCFS)):** The first transaction to be accepted from $A_i$ queue will always have the right to commit all values in its write set $w(C_a)$. Any later transaction whose write $w(C_b)$ set overlaps with the first is immediately terminated. If the two processes write to different channels, there is no collision.

$$A_i \xrightarrow{\text{fail/terminate}} \ x(w(C_{a_i}(k,v))) \xleftarrow{\text{w}(C_b)} C_a$$ (4)

**Proof of absence of write conflicts:** By writing serially there will be only one causally obtained value of each $k$, $v$ at the end of the transaction, which remains unobservable except by the handler. The handler can promise that no values written by some other process, between the start and the end of a given transaction, could have been seen by random selections of clients, since all such values are unobservable until after resolution. Thus we need to show that all values made public are fairly available to any client that attempts to read them, after the transaction has completed, and that no other transaction started since could have altered this sequence.

Data that need to be written by a command are written immediately into the channel’s private namespace, and thus remain unobservable unless promoted to one or more other channels, e.g. default channel, debug channel, etc. by a successful FCFS completion, or purged after all possible use has expired.

**G. Avoiding indeterminacy due to push based semantics**

In Computer Science, push-based update events (‘impositions’ in Promise Theory language) are almost universally adopted as the model for signalling changes. With push methods, agents who intend a change implicitly assume that their intent will be immediately respected in the final outcome. In other words, they can bank each change and proceed with impunity. It’s hard to come back from walking out on that ledge if others are using the same ledge at the same time. Koalja adopted a message passing scheme of queued notifications along with a separate pull-based publish-subscribe data channel [5], showing how to scale data pipelines with decoupled signalling and data for greater reliability and scalability.

To define a service as a single-valued total function of its inputs, for all times, we need to give meaning to what can be observed by clients and handlers on both the interior (within a private processing context) and on the exterior (shared as a final outcome). Engineering a form of determinism plays a key role here. This is a particular challenge when interactions with the clients may be either short or long in duration relative to the rate of updates. The downstream principle in Promise Theory, which represents local causality, on the other hand, tells us that it’s the recipient service that determines the single-valuedness of the outcome—not the client [14], [27]—and therefore it has to be both the calibrator and arbitrator of ambiguities for such decisions. This includes those that occur in client collisions. The goal is clearly to make such a service handler respect the intentions of the client as much as possible.

In our model, the automated integration pipeline, which spans all clients and data handlers, assigns a globally ordered version number to all new data, using the pull-semantics to achieve several benefits. First, the weak coupling of ‘pull’ encourages fault tolerance and is a natural choke for resolving traffic bursts with single-values semantics. Second, it remains independent and can act pre-emptively as a scheduler. This prevents any hanging hosts from bringing down updates from parallel handlers, and allows auto-recovery (self-healing [24]). Finally, it acts as a calibrator for fair interleaving (as in figure 6) [42], [43], promising a consistent view of temporal order for all clients at any scale of the hierarchy.

The proper timeline of an interaction is as follows:

1) A client $C_a$ pushes its intention to update $(k, v)$.
2) If the handler $A_i$ for $(k, v)$ accepts the write, it selects a uniquely-ordered collision-free context namespace for temporary storage.
3) Accepted writes are locally wait-free, effectively immediate at the handler, but the total wait time for a client transaction with multiple writes is finite and is proportional to some monotonic function of the number of keys involved.
4) There is no impediment to reading from the past cone as long as there is service availability (including caches and replicas). The time to read key values is also proportional to some monotonic function of the number of keys involved.
5) Accepted writes are placed in the next timeslot of the handler’s queues, where they will be interleaved into the timeline by the parent handler, and passed up the hierarchy at each scale until globally ordered at the root. While this is taking place, replication of the independently labelled writes can proceed in parallel, since lower key-value layers do not cache or depend on version data from upper parental layers.
6) Once indexed by the parent hierarchy, the new versions of the transactions updates become available all within a single timeslot of the global clock (i.e. simultaneously as far as the time cone of any new process is concerned).
7) Clients can then subscribe to any channels as soon as data have moved far enough up the hierarchy to be indexed and thus visible for subsequent reads.

In broader terms:

- A policy decides which channels $c$ can be written to by the client.
- Each client writes or overwrites temporary key value pairs $(k, v)$ within its own private space during the handler process immediately and with impunity. The map

$$ (k, v, c) \rightarrow (C_a, k, v, c)$$ (5)
This also allows parents to create partial order based on coarse-grained time intervals, by polling the client queues each time the client queue holds the token for sharing. It records pairs of token counters at handler and parent \( t(A_i), t(P_j) \), thus allowing data from different \( A_i \) with the same \( P_j \) to be partially ordered with respect to \( P_j \).

is collision free, where \( C_a \) is used here to represent the transaction.

- The handler of each \((C_a, k, v, c)\) looks for collisions, i.e., determines whether more than one \( C_a \) intends to change \((k, v, c)\) in a scheduled handler time interval. If so, it selects a winner and returns with a refusal to accept the imposed write to the client.

- The surviving values are queued up by \( A_i(k) \) into a common buffer \( Q(A) \), which is then emptied periodically by the parent pipeline receiver.

What happens after this is a matter for policy. Rejected clients could shoulder the responsibility to retry writing the value at a later time, or the handler could do this on their behalf. Neither possibility resolves the meaning of having two clients attempting to change the same value in the same approximate time-frame, but it resolves the actual collision. The matter of whether two clients should be allowed to change the same \((k, v)\) is typically a matter for access control policy. In CFEngine, attempts to change a value were rate limited with deadlocks, preventing thrashing as an acknowledgment of the spacetime aspect of intentional change [44].

For example, incrementing or decrementing a shared value is commutative and deterministic and easily understood, but overwriting an absolute value with an unrelated value is not commutative and would effectively turn \((k, v)\) it into a random variable. This is not something a service can resolve except by denying access.

A global pipeline policy for enforcing a single-valued coordinate-history at each local agent simplifies and potentially speeds up the reading and writing of data transactions amongst distributed processes, without losing control over the causality of sequences [2]. Each parallel shard or data handler \( A_i \) can follow these process promises locally for local spacetime consistency.

VII. THE NAMESPACE AND ITS PIPELINE SEMANTICS

We can now turn to the problem of integrating the totally ordered writes of individual handler rings into a larger, partially ordered set—sewing together and interleaving the results across a complete spanning tree of the system. This is how a coordinatized namespace can be curated, without consensus voting. The price for such a global order is an increased uncertainty in the defined estimate of ‘simultaneity’, as parallel key writes span a larger and larger total memory space. In other words, the wider the catchment area for data, the coarser the temporal uncertainty of snapshots according to the wall clock. This is an unavoidable and fully expected expression of the usual Nyquist-Shannon sampling law, for any steady process (see section VIII-B). As a side effect of deterministic correctness, consensus is a once and for all operation that minimizes communication. In a quorum solver, excess communication is required to determine a value and communication is expensive (in terms of energy as well as latency).

A. Hierarchical cooperative partial order

Let’s return to our client \( C_a \), whose transaction job refers to key-value pairs located across many \( A_i \) from every part of the system. The client submits its transaction-related operations to individual handlers \( A_i \) that own specific \((k, v)\) pairs.

\[
C_a \xrightarrow{+(k,v)} A_i \in G(A) \quad (6)
\]

\[
A_i \xrightarrow{-k \in k(A_i)} C_a. \quad (7)
\]

A scaled version of the local selection procedure has to keep the same promises of the local solution: i.e. to only read or observe data from the past cone globally, and to totally order parallel intervals (now of increased duration). We therefore scale proper time using a hierarchy of handlers, each with their own local time. A hierarchy is an addressable structure across spacetime, which can be compared to the addressable structure of the Internet’s Routing or Domain Name Services. The more global the answers we need the higher up the hierarchy we need to go to find root nodes with large scale indexing. For actual data, we use the index to go straight to a local service handler \( A_i \).

The scenario is still that shown in figure 1. We divide up the whole of spacetime into cells or rings of \( A_i \) handlers, which all perform an analogous function on a shard of mutually exclusive data. Each agent works independently on its own data, but when it comes to committing writes, the agents in a ring now take turns to interleave their commits into the global records. Each ring has a single parent, which polls its children in turn to interleave finished writes. The writes have been labelled with the proper time \( \tau(A) \) of their own storage process, but we have no idea how these are related to one another for different \( A_i \). Thus, the parent has its own version counter (clock), which

Fig. 6: Data from parallel handlers can be interleaved for indexing.

HE NAMESPACE AND ITS PIPELINE SEMANTICS

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Fig. 6: Data from parallel handlers can be interleaved for indexing.
calibrates all the interleaved commits from the children by committing its own record of the association. It collects all keys written in a given handler time slot into a serial timeline of its own, labelled by parent time (see figure 6). Each write happens locally and immediately, but a globally accessible record of it may take some time to propagate out to the whole of a space to form a complete snapshot.

B. Queueing commits for publication

We can now walk through the mechanics of the process of publishing committed writes explicitly. The service agents form a collaborative hierarchy formed from edge handlers \( A_i \), parent handlers \( P_j \) (see figure 1), grandparents etc. These are collected into groups or rings at each level, which interleave records from handlers at a lower level by pulling them in batches from the queues assembled continuously by the handlers. This secures a decoupled pre-emptive schedule for updating temporal order at the next scale. At the handler level, all agents continue to resolve data read and written locally, without waiting; however, a token \( \tau \) is passed around each ring by the parent. The parent shifts its from subordinate to subordinate to ensure fair interleaving of data in a round robin fashion. If a client is unavailable, the parent can skip it temporarily while it recovers. As long as the cycle spins with the same orientation, the integrity of the interleaving will be maintained.

\[
\begin{align*}
\text{define: } & j := (i + 1) \mod N(G) \\
A_i & \xrightarrow{+D(u_k) \mid \tau(G) \in (i\tau(G) \mod N_G)} A_j \\
A_j & \xrightarrow{-\tau \rightarrow} A_i 
\end{align*}
\]

The latter is equivalent to promising to commit transactions if and only if the group proper time lies within the agent’s appointed time slot.

\[
A_i \xrightarrow{+D(u_k) \mid \tau(G) \in (i\tau(G) \mod N_G)} Q(A_i), \quad (11)
\]

Committed records are added to a log or queue \( Q(A) \) by the handler, denoted \( Q(A_i) \), which is drained in batches by the parent whenever a child has the coordination token. This pattern is replicated up the hierarchy. At the top of the hierarchy, a root service node promises the global time index, somewhat analogous to a root DNS record, or master routing table.

\[
R \xrightarrow{+(k,t(R),t(A_i))} *, \quad (12)
\]

A purely voluntary scheme of cooperation is not pre-emptive, and can easily be interrupted or sabotaged by a failed or floundering node. A pre-emptive approach can be secured by using each parent as the arbiter of token ownership: since the purpose of the token is to secure the exclusive attention of the parent; listening to agents one at a time by pulling (uploading) a pre-packaged queue \( Q(A) \) of completed commits for the timeslot.

\[
P \xrightarrow{-D(u_k) \mid (\tau(G) \in (i\tau(G) \mod N_G))} Q(A_i) \quad (13)
\]

The conditional is now evaluated by \( P \) not \( A_i \). No push-based (imposition) scheme can be reliable due to the FLP result. This could potentially add an unwanted communication delay to hand over. However, this only affects the slot for uploading (and thus publishing) commitments to \( P \), not their positioning within the schedule for updating the past cone, which continues to be updated in parallel at best possible speed. Thus, the serialization is only in the publication schedule, not in actual data processing. We can therefore examine the failure modes of a single handler as a decoupled issue.

In general, secure behaviour by every \( A_i \) has to rely on the fault semantics of process handling by \( A_i \), which is beyond the scope of this discussion. We assume that \( A_i \) does not break any promises to the client or parent during its timeslot, in case of failure. One way to ensure this is to make updates based on synchronous reliable transport [20].

The final resolution mechanism is roughly analogous to that used by the DNS service for IP addresses, but unlike DNS the parents don’t reveal their clock versions downwards to synchronize \( A_i \). If the \( P \) offered their time as a service, this would add unmeasurable delays, since \( A \) doesn’t need the value of \( P \)’s clock as long as service integrity is maintained (it would be similar to using NTP to try to synchronize the clocks of the parallel clients, and with the same flaws). Instead, the parent keeps the index association between \( k, v_n, t(a) \) and \( t(P) \) as an aggregate log. This adds a scaling burden, since the parent keeps records from all children and thus needs to work faster to compress them into the same interval. The result is that the resolution of the past cone is eventually reduced by greater spatial coverage. The interleaving is not linear, so we might not notice for sparse probabilistic writes, whereas we might notice for bursts of consistent updates. In any event, the timeline will be ordered properly but the certainty of being able to see the latest updates will become worse as traffic increases.

Once ordered, it’s a simple matter to ensure a consistent published view of shared data, by curating monotonically versioned streams, labelled by data’s origin or source handler \( A_i(k) \).

C. Key handler \( A_i(k) \) semantics

The edge handler lives at the edge of the network. Data need not be transported from this edge except for long distance replication. We can now combine all the foregoing pieces into an algorithm at \( A_i \):

1) An agent \( A_i \) writes uncommitted records without delay, using the current local clock counter to record the moment of writing. It’s possible for several records to end up with the same timestamp. The channels’ commit policies promise to resolve such collisions and signal their acceptance of rejection of certain

\[6\] The contentious aspects of availability have to do with the timescales involved in processing. All data are subject to eventual consistency for different observers, as they spread out into the future cone.

\[7\] Note that nomenclature differs here between databases and version control systems. We use ‘commit’ in the sense of a database here, not in the sense of a version control system, where the term ‘push’ might be used.
transactions.

\[ C_a \xrightarrow{+(k,v)} A_i \]  \hspace{1cm} (14)
\[ A_i \xrightarrow{-(k,v)} C_a \]  \hspace{1cm} (15)
\[ A_i \xrightarrow{+w(k,v,m)} (k,v) \]  \hspace{1cm} (16)
\[ A_i \xrightarrow{+D(k,v,c) \text{policy}(k,c),(k,v)} P \]  \hspace{1cm} (17)

The parent node accepts the schedule timeline, where committed writes \((k,v,c,t_c)\) represents a version change for the key \(k\) in channel \(c\). The parent node proceeds to make the committed version available for expanding searches:

\[ P \xrightarrow{+D(k,v,c)} \ast \]  \hspace{1cm} (18)

These updates spread like ripples around the system, gradually becoming visible to all.

2) The index at \(P\) associates a unique authoritative home \(A_i\), with a unique key for a data model, as well as a list of replicas by region.

3) A separate index per channel associates the graph of temporal order with key version updates, thus allowing clients to walk through the data in curated temporal order.

4) If we want to be able to promise and recover temporal order over all locations, then we need a process such that the future cone is unique. The parent node for \(A_i\) maintains an index by group time \(t_c\), and by key \(k\) that will be published upwards for global view, so that searches point to the authoritative handler for each key. The parents thus store the authoritative order of records within their group.

5) As we go further up the hierarchy, the chance that records will need to order relative writes on different \(P\) regions grows progressively more unlikely. So the amount of sequential intent should fall off appropriately.

It is up to a transaction handler to go as far up the hierarchy as necessary when writing correlated sequences.

The parents can also checkpoint the \(A_i\) clocks to its own to speed up searches of older data.

6) Once committed and published, independent replication processes can be used to speed up access and maintain probable availability across large areas. Pull based replication (subscription) allows greater reliability and scale predictability than push based replica methods [43].

D. Parental Pre-emptive Bulk Indexing

With a queue buffer we decouple publishing of committed records from the actual act of commission, using voluntary cooperation as the link. This offers both security and efficiency for the predictable schedule [14], [42].

The batch update schedule is as follows (see figure 7):

- At any time, agents write data \(k,v_n\) to private workspace, where \(n = t(A)\).
- Each record in the committed chain of versions can be joined in a chain to its predecessor \((k,v_{n+1})\) to make search efficient (see section E). A graph representation
- After collision avoidance, an agent \(A_i\) adds a committed write to the queue \(Q(A)\) as a record \(\sigma_A = (k,t(A),c,i)\), which is complete pointer to \(v_n\). Note that the record contains the agent for the key in short form \(i\), since the sequence will not proceed without gaps for the timeslots.
- As \(P\) receives a batch \(\Sigma_A\) of completed records with pattern \(\sigma_A\), for the interval, it associates this batch with its own timestamp: \(\sigma_P = (t(P), \Sigma_A)\) and appends that to its data, and adds it to its pipeline queue \(Q(P)\) to be received by \(R\).
- As \(P\) receives a batch \(\Sigma_P\) of completed records with pattern \(\sigma_P\), it writes the association \(\sigma_R = (t(R), \Sigma_P)\), and so on.

E. Retrieving ‘latest’ data from the hierarchy

Unless specific version numbers are referenced in a search, we propose the default search policy to be that:

1) Any transaction refers to one and only one version of a given key’s value chain for its entire execution, namely the last value written prior to the start of the transaction.

2) If a transaction alters values during the course of its execution, it writes these changes to private versions of the that shadow the initial value, to be committed at the end. Intermediate values are not seen by other processes.

The need to walk through every key, and thus reconstruct the entire past cone of a certain transaction may be necessary. In order to find members of the causal past from a given transaction, a transaction consults the root node (perhaps via a directory service), which assesses the current starting \(t(R)\) of the transaction, and uses this to parse the tree of associations.

Index services, for known key values, can enumerate the keys, find their key handling shards \(A(k)\), and pick the latest version corresponding to \(v_n \leq t(R)\). Resolving this inequality quickly will depend on the data indexing on the parents. Starting from the top down is efficient since the ordered records of the parent hierarchy associate all key changes with a single valued time, starting from \(t(R)\).

All this depends on how often the version data are changing. Such a confluence of searches on the index data can be shared by a farm of search agents, since the data are read only during searches.

More commonly, transactions will want to know the latest consistent cone. We need to parse the associations. This has to be quick.

Determining the precise order of any two versions belonging to different \(A_i\), we need to compare their timeslots in the relevant index:

\[ v > v' \iff (v_R > v'_R), (v_P > v'_P), (v_A > v'_A). \]  \hspace{1cm} (19)

As far as lookups are concerned, the virtue of a hierarchy is that it naturally load balances the lookup information as long
as we know which node to query in order to resolve times. However, we must also acknowledge that treelike hierarchies are brittle structures and failures have to be offset by redundant replication on all levels. Reliability on a massive scale is not cheap.

Remark 2 (Synchronizing clocks with NTP?): The difference between this scheme and simply deploying NTP on each host is that we ask the $A_i$ to take turns in a monotonic round robin cycle. This allows them to predict positions within a fairly interleaved schedule. A small number of slots may be allocated between the interleavings to ensure that a sudden burst would not block. Thus, this is a form of pre-emptive scheduling. No single host should be allowed to block others, else the system becomes vulnerable to denial of service attacks.

E. $n$-torus clock

In the main presentation, we have used the ring structure for interleaving parallel write processes. This is a key scaling process, which benefits from a cyclical structure. Another process that can benefit from a cyclic structure is data consensus and replication, which is often handled by Paxos or Raft in contemporary thinking. Rather than these complex protocols, a simple approach would be to transparently use reliable transport [20] to pass copies of write operations around a ring of replicas. Once a data update returns, the replication will be consistent and the ring acts as another observability brake (like transparent copy on write). If we add this, then we now have two rings, or a 2-torus:

1) Shard ring (concurrent interleaving).
2) Consensus ring (copy on write).

With both of these dimensions, after a complete cycle in both directions, we know that data writes are replicated and ordered for publication. Indeed, other constrained processes, like multiple schema collections, models, and tabular types, can be decoupled in a similar way, leading to an $n$-toroidal clock. The motivation for this is to avoid unnecessary waiting. It can be shown that the two dimensions above are sufficient however.

The precise behaviour of a data pipeline must be attuned to the particular application use-case in question. In current thinking, databases are generic contraptions tuned for one and only one mode of usage. This is one reason why we need so many different kinds of database. However, if users ‘stated their intentions’ as policy up front, then the backend system could accommodate and interleave multiple needs. This kind of thinking is growing in popularity.

VIII. Scalability of the Clock

There are many open questions in describing the proposed service model, but we can make some remarks about the scaling rates.

A. Granularity of clock layers

Our data pipeline ‘clock’ is driven from the bottom up, client requests determine the amount of data flowing up to the root nodes. The size of the data propagating up the pipeline is a concern for the stability of the service. The application context will determine the stress on the system for ‘mostly write’ or ‘mostly read’ regimes.

As associative timestamps move up the pipeline, no actual data need to be moved, so each association is a small amount of data. However, each layer packs in data from parallel sources, so the total amount may still be large. Moreover, the timespan (as perceived in client time $\tau(C) \sim t(A)$) of each ordered batch or uniquely identifiable snapshot grows by an order of magnitude for each layer of aggregation. The ‘thickness’ of
We can find single values quickly from their handlers. In other words, when involving multiple keys with times that were varying levels of precision in a scale-dependent way, because the accuracy in time is proportional to confinement in space.

We define the maximal past cone for a transaction to be that history, with associated inputs from $t(A), t(P), \ldots$. In practice, a complete spanning tree of associations is only needed when reconstructing a search that involves multi-key temporal order. We can find single values quickly from their handlers. In other words, when involving multiple keys with times that were correlated over spatial separations, the spacetime trajectory of the past-cone updates has to use a shared proper time as the search parameter. By contrast, the temporal order for a single key is always determined by $A$ alone.

When searching for the past cone, each handler may thus have a chain of versioned indices over its children to traverse. In order to find an index that covers the complete observable cone of the process, starting from $A_i$ a broken thus follows the chain until it reaches a node in $S^n$, whose clock presides over all the subordinates.

By the downstream principle, a receiver of data is always the arbiter of its interpretation: i.e. its value, its time stamp, etc. So, if some $P$ sends to $A$, then $A$ decides its current value. If $A$ sends a value to $P$ then $P$ decides its current value. The assumption in using higher levels to adjudicate time for lower levels is that the delays incurred by association are unavoidable. This may be hard to accept for engineers who still believe that latency is a bug rather than a feature of communication; however, one cannot make progress without accepting this as an unavoidable fact of communication. The best any system can promise is that the publishing of committed results moves from bottom to top monotonically, and thus the fully shared interpretation of absolute past (however delayed) is only published as a single version for all of space (at the same logical moment) by the top node.

B. Spacetime sampling resolution

A final point about the coarse graining mentioned in the previous section. We can interpret this as the Shannon-Nyquist theorem’s fundamental limit on the observability of periodic spacetime processes [29], [45]. For steady state processes, we can decompose update cycles into Fourier series and compute a fundamental uncertainty relation. This corresponds to the well known Heisenberg uncertainty in quantum mechanics [46]:

$$\Delta \omega \Delta t \geq S$$ (23)

**Lemma 1:** We can define the past cone for a record with varying levels of precision in a scale-dependent way, because the accuracy in time is proportional to confinement in space.

We define the maximal past cone for a transaction to be that generated by records in $t(R) + \Delta t(R)$ so we need and indexing function that takes a current time for a service handler and returns the head of its past cone:

$$f(k, t(A)) \rightarrow (k, t(R)),$$ (24)

since the sequential log starting from $t(R)$ points to all subordinate versions across its spatial catchment area, by virtue of the single aggregation pipeline’s process gradient.

**Lemma 2:** All this amounts to a coarse grained foliation into spacelike hypersurfaces, where the thickness of the surfaces is determined by the cycle period at each level.

$R$ points to the head of the past cone for each key’s write history, with associated inputs from $t(A), t(P), \ldots$. In practice, a complete spanning tree of associations is only needed when reconstructing a search that involves multi-key temporal order. We can find single values quickly from their handlers. In other words, when involving multiple keys with times that were correlated over spatial separations, the spacetime trajectory of the past-cone updates has to use a shared proper time as the search parameter. By contrast, the temporal order for a single key is always determined by $A$ alone.

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C. Self-governing rate-limiting for thrashing protection

As with the self-governing, rate-limiting architecture in CFEngine [44], each agent’s promises ensure that it is immune to client traffic bursts. We make handler acceptance conditional on the work queue, i.e. handlers accept transactions provided the write commit queue is not too long:

$$A_i \rightarrow \left| Q(A_i) \right| < L \rightarrow C_n,$$ (25)

where $|Q(A_i)|$ denotes the length of the queue, and $L$ is some configurable policy for maximum length.

The interleaving of data by the parent is essentially a packing problem. In average operation, writes may be relatively sparse and packing is conservative. However, busy data pipelines may integrate large amounts of regular data from a known list of sources leading to a dense and continuous stream of writes. The most challenging integration problem will be when every thread is writing new data in parallel to different keys, so that each parent update involved in the interleaving is fully packed. This could overload the input queue of the parents. However, one could brake the process naturally by waiting for the parent records to be written on commit before ending a session. Rate limiting of connections may be necessary in any service to avoid queue divergence.

This packing process places a burden particularly on the root nodes of the hierarchy. The flow limitations implicit in this packing make the root node (including its replica set) the ultimate choke point for data flows. If they can’t keep up with write versioning, the global index will fall behind. By ensuring the emptying of the queue by pulling, and the refusal of connections when the queue is full, this limitation propagates back down as an autonomic throttle for self-protection.

**Remark 3:** If key changes are in different shard handlers $A_{j \neq i}$ then they can still occur in the same public time interval, i.e. within the same coarse time tick, but if they are repeated keys, they must be serialized, so we need a consistent way of serializing locally, and aggregating in parallel—quickly, and with no limit on spatial separation. These changes can be labelled in the same version intervals, but we have no way of
knowing when clients will see these update, because observation depends on both the promises of publishing (+) by the service and subscribing (-) by the client.

The parent only has to receive data that are finally committed to different channels. This may be bursty. These updates don’t need to fall in the trap of push updating. They can be queued on the At themselves and be pulled at the parent’s convenience with a fair interleaving policy [5], like a managed data pipeline, thus avoiding the perils of push imposition semantics. Since publication of committed transactions is performed by the parents, there is no danger that data will become unsynchronized. Moreover, as long as the number of channels is limited, there will be a natural rate limiting effect from handling contention.

For example, an agent could write to a different channel at a future time, but is not allowed to win a ‘latest’ race by teleporting into the future. These are the semantics of the default channel.

IX. DISCUSSION ETC

In this paper we’ve written down a deterministic interleaving process for clocking proper process time over a spanning network of data handlers [2], in which the propagation of key value versions is automated, following the principles well known in Internet address scaling. The role of our hierarchical ‘clock’ is to assign unique but distributed coordinates to what amount to CRDTs, thus decoupling the processes in a data lifecycle: capture, replication, committing, publishing, and searching, and ensuring that every search will always see the consistent causality cone intended by the writer.

Much of the reason for trouble in handling the scaling of time order lies in the almost universal adoption of push based semantics, which are unreliable and expensive to adapt, and the belief that such operations are instantaneous (impositions in Promise Theory language) as described by (6). In a push scheme, data arrive in an uncontrolled manner at a service point, where an escalation of resource ensues to try to cope: increased queue lengths, load sharing dispatchers, intermediate agents, etc. The rational alternative to this is the Publish-Subscribe or Pull based methods used by Content Delivery Networks, where directory services assign queue handlers, and clients help-themselves in a self-service lookup.

The alternative algorithmic implementations of a global proper time, described earlier, use transported tabular memory to count ticks with ‘tensor clocks’, or tables that accumulate path history as the process propagates from agent to agent by virtual motion [4]. Scalar, vector, and even matrix versions of computing, including the development of the infamous services process. Our alternative uses a distributed counter like a stigmergic clock, which doesn’t resolve all the ambiguities of distributed counting. In a sense, our alternative uses a distributed counter like a stigmergic process.

We anticipate this coordinate namespace to be especially important in highly distributed applications, such as edge computing, including the development of the infamous services as part of 5G and 6G wireless networks. Maintaining speed and locality of service, but with far reaching access, is the optimal way to scale data services. Today, long distance data flows are a major cause of IT’s carbon footprint, which is unsustainable for the expected growth. In that sense, what we describe here is a universal infrastructure for data services, which scales both predictably and as reliably and efficiently as can be with current technology. The approximate intuitions of the so-called CAP Theorem are then surpassed by a mixture of deterministic correctness and redundant best-effort availability, thanks to our abandonment of strong coupling quorum semantics.

One should never underestimate the cost of maintaining structural information on a large scale. There is no free lunch, as they say. A partition is a partition. Redundancy is costly, and intrinsic latency is unavoidable. In this scheme, garbage collection of temporary writes (CRDTs) will be an important part of keeping a data field operational for long durations. This is another under-addressed problem, though in our cyclic design, this is a simple matter to automate through scale-dependent policy. Our aim, with this composite approach, is to minimize communication and unnecessary transport of data, which both have a high energy cost. The ability to replicate state with ‘Just In Time’ streaming of just the necessary dependencies is a realistic alternative to extensive caching, and this could be optimized with machine learning enabled smart caching. Many details remain that we’ll return to in future work.

Parts of the discussion in this paper are embodied by the patents US K1093PCTUS and EU EP3794458A1.

APPENDIX

A. Promises

We summarize some notations and terminology for convenience in figure 8. We use the notation of [27] in which an agent A makes a promise to another agent A’ with body b, which describes the nature and magnitude of the promise:

\[ A \xrightarrow{+b} A', \]

where a + sign denotes an offer. An imposition is an attempt by A to opportunistically induce a response in A’, without prior warning, and is written with a ‘fist’ arrow:

\[ A \xrightarrow{+b} A'. \]  (27)

If the subject of the promise or imposition is accepted by A’, a corresponding − promise is given, denoting a causal binding from A to A’:

\[ A' \xrightarrow{-b'} A. \]  (28)

The extent of the coupling is b ∩ b’. If a promise of b is conditional on the receipt of promised conditions c1, c2, . . . , then we write

\[ A \xrightarrow{+b|c1, c2, . . .} A', \]  (29)

The arrow notation is convenient to draw in figures, such as figure 9.

Every shared service wants to utilize its resources as efficiently as possible by multiplexing shared flow bottlenecks in an optimal way. Thus key-handlers promise fair policy-based multiplexing for access to keys.
A data registration or 'commit' operation finalizing a number of write operations

An intended primary key name for a data record (always invariant)

The invariant handler agent for key

The most recent (head) version of \( v(k) \).

A data channel. The default channel is ‘latest’.

The current value of the private proper time at agent

The current value of the exterior, shared proper time for group or agent

A data value for key

A write of value

A read of value

The current value of the exterior, shared proper time for group or agent

A clock association for a key update, a tuple \((k, t(A), t(p), v_n)\)

A commit set of associations \( \sigma_i \) passed to a parent from \( A_i \)

The concept of a transaction is often confusing to those who don’t work in database jargon. A transaction is not an atomic write, but something closer to a closed function in programming.

**Definition 11 (Transaction):** A protected ‘quasi-atomic’ unit of work, or a single command issued to a data service, which may be viewed a sequence of data operations and ends with a ‘commit’ operation. A transaction is sometimes considered to be reversible, though we shall not assume this.

Note we say quasi-atomic because transactions are not indivisible, they are only wrapped as black box changes, whose interior machinations are unobservable.

### C. Timescales

Time plays a key role throughout any communication system. We deal with not only a variety of processes but also a variety of typical scales for interaction. Clocks are used almost everywhere for computation, but the common notion of time as we see on the wall clock (or UTC in the digital era), is not the clock we need. A clock is any reference process with different identities and semantics.

The major functions of a clock are:

- To resolve the partial order of events by counting faster than the phenomenon of interest, according to the Nyquist law.
- To define the cone of absolute past, and
- To be able to reconstruct a snapshot of the current spatial hypersection, which is what we understand as a ‘snapshot’ of the data.
Proper time is the time counted by an agent that executes the steps of a local process with its interior resources [14]. When processes are distributed, the counting of proper time moves from agent to agent, along the trajectory of the process (as with vector clocks). We may further define this to be the ‘intended’ order of events since it is co-moving with the origin process and represents the order in which data were sampled and submitted for archiving—straight from the process’s mouth, so to speak [48]. Is the time defined by the recipient of the data or the imposer of the data, i.e. compare expressions (6) and (7). This was referred to as GDO and GWO in the language of [48].

We define \( t(A_i) \) to be the value of an atomic counter at an agent \( A_i \), which increments for every change operation, and thus represents its proper time. If lost, the counter could be recovered by a record scan (analogous to fsck in Unix).

Orders of magnitude in terms of UTC time are helpful to gauge the effect of a distributed system on the human world. For example, the timescales for common operations:

1. A direct indexed read, taking milliseconds \( C \xrightarrow{\text{+r}} A \).
2. A direct indexed write, taking milliseconds \( C \xrightarrow{\text{+w}} A \).
3. A search and computation leading to reading multiple values, taking hours, involving many agents.
4. A search and computation leading to writing multiple values, taking hours, involving many agents.

The range of timescales over which searches and computations preside represents a challenge for giving meaning to multiple process channels in the face of parallelism. While reads and writes take only a short time, complete transactions that rely on a consistent view of data make persist for many hours.

In general writing data is more time consuming than reading data, since reads can be parallelized, while writes to a common location can only be performed serially as a FIFO queue. Thus, some processes are optimized for mostly-writing data, some for mostly reading past data, some always want the latest value (even during a storm of updates), and various admixtures of these extremes.

When many short data writes overlap with a long sequence of reads that compute a result, the changes to the read set could potentially skew the result. Whether this is right or wrong depends entirely on the intent of the data operation.

In our system for interleaving data with ‘round robin’ scheduling, there are cycles used to coordinate relative order by shared timekeeping. The time allocated to each computer in a cycle before handing over to the next is (in principle) a configurable policy choice. We want this cycling to be at a quick steady rate for interleaving busy transaction queues. Unlike a wall clock, a version system doesn’t need to count artificial changes to measure an independent time in between changes: it only needs to increase the shared time counter when a change arrives. However, no harm is done by counting at a regular rate, since records will typically record UTC time for convenience if they need to.

### D. Spatial scales

Space is a representation of memory in a computation. Each addressable location involves physical and logical extent. We are interested both in geo-spatial extent (which informs us about physical latency) as well as the space of logical key values, which is relevant algorithmically.

In semantic spacetime, locations are agents that can keep promises, i.e. exhibit functional behaviour. We can think of them as software programs or self-contained processes. Logical or semantic scales form a hierarchy, as levels denoted by \( S^n \) in semantic spacetime [35]. A collaboration of agents at scale \( S^n \) may be thought of as a single agent at scale \( S^{n+1} \).

At the edge of the network (level \( n = 0 \)), the collection of all clients processes may span the entire globe or beyond. However, they interface with a much smaller number of service points which are scattered around the catchment areas.

Some databases use front end ‘controller nodes’ to mediate a connection with specialized shard handlers. Equally, client libraries could mediate the connection directly from the client side. Thus, in this note, we do not discuss the role of the client or service brokers, as we are concerned mainly with the behaviour of shard handlers.

A local group of handlers \( A_i \) is written \( G(A) \) and is assumed to be co-located on the scale of a single datacentre, while parent nodes may exist at a datacentre level, grouped across a city at level \( G(P) \), to a region level, a country level, and so on. There’s no limit, in principle, to the scale to which a system might expand—though eventually the burden of tracking a single process must grow beyond acceptable limits.

Naming often gets in the way of more general progress: some may refer to ‘scaling up’ versus ‘scaling out’, horizontal versus vertical scaling, and so on. These terms serve to distinguish meanings in a local context, but general principles are often elusive. The term ‘top down’ means from a global view of time, and it starts from the ‘root’ node for a span of the system. Conversely, ‘bottom up’ means a local view of time, which is begins at the edge or leaf nodes of the system span. What one would refer to as scope in software engineering, for process encapsulation of operations and transactions, is sometimes called an isolation level is database parlance.

### E. Semantic spacetime

Semantic spacetime is constructs processes from four basic spacetime relations: i) FOLLOWS (for temporal order), ii) CONTAINS (for spatial aggregation), iii) NEARness for location or semantic equivalence, and iv) EXPRESSES for scalar value expression. The structure of a namespace coordinates can be summarized for our causality cone with the following promises:

\[
A_{i+1} \xrightarrow{\text{+FOLLOWS}} A_i \quad \text{(rings)} \\
v_{n+1} \xrightarrow{\text{+FOLLOWS}} v_n \quad \text{(versions)}
\]

(30)
\[ A_i(k) \xrightarrow{\text{CONTAINS}} k \quad (\text{key-value}) \]
\[ (k, v) \xrightarrow{\text{EXPRESSIONS}} \{v_n\} \quad (\text{version strings}) \]
\[ A_i \text{cache} \xrightarrow{\text{NEAR}} \Sigma A_i \quad (\text{replicas}) \]
\[ \sigma_i \in \Sigma A_i \xrightarrow{\text{NEAR}} \sigma_i \in \Sigma \quad (\text{simultaneous}) \]
\[ T_i(w(k)) \xrightarrow{\text{NEAR}} T(w(k)) \quad (\text{overlapping } T_i) \]

(31)

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