Decoupling conflicts for configurable resolution in an open replication system

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ABSTRACT

replikativ is a replication middleware supporting a new kind of confluent replicated datatype resembling a distributed version control system. It retains the order of write operations at the trade-off of reduced availability with after-the-fact conflict resolution. The system allows to develop applications with distributed state in a similar fashion as native applications with exclusive local state, while transparently exposing the necessary compromises in terms of the CAP theorem. In this paper, we give a specification of the replicated datatype and discuss its usage in the replikativ middleware. Experiments with the implementation show the feasibility of the concept as a foundation for replication as a service (RaaS).

Keywords

CRDT, eventual consistency, strong consistency, CAP theorem, middleware, replication, RaaS

1. INTRODUCTION

While building scalable distributed systems, developers are typically confronted with a number of (potentially conflicting) requirements:

1. Never lose data!
2. Always be available! Even when offline.
3. Provide a simple API preferably with explicit consistency semantics, e.g. DVCS-like, and not a distributed file system without history, such as dropbox. Keep a sequential and consistent log of all modifications.
4. Support cross-platform serialization while offering strong and extensible data semantics. Do not tie users to a single platform, e.g. JSON and JavaScript.
5. Replicate everything at once consistently: code, data types and referenced binary values.
6. Do not require configuration of complex backend storage for simple applications.
7. Avoid ad-hoc reimplementation of network code with every application and framework.

In our replication system, replikativ, we combine a number of technologies to meet these requirements. The main idea behind replikativ is to decouple the replication of data from the application code, so that different applications can share the same data base without mandatory agreement on how the data is managed. This allows to fork application state and innovate with new applications inside existent user bases if the data is shared openly. Recent advances in machine learning techniques, e.g. deep learning [1], highlight that access to large amounts of data can unlock new insights into different aspects of the involved processes and allows to evolve smarter services. As of today, the notion of open-source is often applied to code, while data is considered as the property of individual providers and only evaluated in their own interests. The greatest potential of building shared data and knowledge bases is yet largely untapped.

To provide users with sovereignty over their data, replikativ will support a public-private key encryption system and our design already reflects that. It does not rely on the often false security assumptions of a safe internal zone versus the internet and instead will encrypt the data end-to-end and not only the communication channels.

In this paper, we focus on one technical core component of replikativ. We designed the system around a new datatype, named CDVCS, which decouples the conflict resolution mechanisms which are typically hard wired in convergent replicated datatypes (CRDTs) [8]. The contribution of this paper is the documentation of this new datatype and its combination with different conflict resolution strategies. Originally inspired by [6], we use CDVCS to implement the important concepts of a distributed version control system (DVCS) to retain convergence and scalability in our replication system. We have generalized replikativ furthermore to allow novel

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combinations of CDVCS with arbitrary CRDTs by snapshot isolation. This provides the developer a flexible design choices for different trade-offs between consistency and scalability of write operations.

2. RELATED WORK

The design of CDVCS trades high availability for weaker consistency guarantees. It is motivated by two major lines of work: distributed version control systems (DVCSs) and confluent replicated data types (CRDTs). For a general overview of consistency conditions and terminology, we refer to the survey of Dziuba et al. [4].

2.1 DVCS

Today’s work flows for light-weight and open-source friendly software development are centered around distributed version control systems (DVCSs), such as git, mercurial or darcs. Updates and modifications can be executed offline on the developer’s local replica(s) and are synchronized explicitly by her to the shared code base. In terms of the CAP theorem [5], these systems provide availability, but allow divergence between different replicas. To reconcile the system state, some after-the-fact conflict resolution has to be applied, e.g. through 3-way-merging mechanisms on text files or conflict markers in case of non-mergeable differences. These conflicts then have to be resolved manually. To support the user, DVCSs provide a commit history which allows to determine the order of events and and detect when consistency has been broken by concurrent writes. While this technique has proven very effective for source code, attempts to transfer these systems to data have had limited success so far. Prominent examples are file systems that have been built on top of git, such as gitfs or git-annex. There have also been repeated attempts at using git directly to implement a database. Data management systems built on top of off-the-shelf DVCS exhibit a number of problems:

1. Programs can exploit their text-oriented conflict resolution scheme by encoding the data in text format, e.g. in JSON. However, this requires serialization in line-based text-files in a filesystem structure to be compatible with the default delta resolution mechanism for automatic conflict resolution. When the diff’ing of text files is customized in any of these DVCSs, usually a complete reimplementation of operations becomes necessary, and the desired compatibility is lost. Instead of relying on textual representation, we believe that providing customized data types with principled conflict resolution schemes is a more natural approach [9].

2. File systems are the historic data storage model for a non-distributed low-level binary view on data within a single hierarchy (folders), and hence cannot capture and exploit higher-level structure of data to model and resolve conflicts. Today, the preferred way to manage state from an application developer perspective is often a relational model or language-specific data structures as they are declarative and allow to focus on data instead of file system implementation details.

3. DVCSs often do not scale when it comes to handling of binary blobs as they take part in the underlying delta calculation step. For example, git then needs an out-of-band replication mechanism like git-annex to compensate, adding additional complexity to the replication scheme.

We think that these attempts based on DVCSs, while being close to our work, are doomed to fail due to the trade-offs captured by the CAP theorem. They try to generalize a highly optimized workflow of a manual low frequency write-workload for development on source code files to fast evolving high frequency write-workloads of state transitions in databases. Much better trade-offs can be achieved by picking the important properties of a DVCS and composing it with other highly available data types. This approach allows to build scalable, write-workload oriented data types at the application level.

By building on the CDVCS, we can use other more efficient confluent datatypes for write intensive parts of the global state space, e.g. posts in a social network and indexes on hashtags. A DVCS introduces considerable overhead and potential loss of availability on these operations.

2.2 Confluent replicated datatypes (CRDTs)

While the original motivation for our system was to implement a DVCS-like repository system for an ACID database in an open and partitioned environment of online and offline web clients and servers, a replication mechanism was lacking. DVCS systems like git track only local branches and do not allow propagation of conflicts and hence have no conflict-free replication protocol. Conflicts can show up in any part of the network topology of replicas during propagation of updates and can only be resolved manually at this position. Since the system has to stay available and needs to continue to replicate at scale while being failure-resistant, we decided to build on prior work on convergent replicated datatypes [8]. CRDTs fulfill our requirements as they do not allow and need any central coordination for replication. They also provide a formalism to specify the operations on the datatype and prove that the state of each replica always progresses along a semi-lattice towards global convergence. CRDTs have found application e.g. in Riak3 or soundcloud to allow merging of the network state after arbitrary partitions without loss of write operations. This is achieved by application of so called downstream operations on the respective local state of the CRDT. These operations propagate as messages through the network. While this fits our needs for the replication concept, it does not provide semantics for strong consistency on sequential operations.

The notion of a CRDT in general implies automatic merge-ability of different replicas and does not lead to conflicts which then would need some centralized information to be resolved. Hence, they are usually referred to as conflict-free replicated datatypes. Our datatype somewhat breaks with this strong notion by merging conflicts, emerging as branch heads, from the replication mechanism into the value of the datatype. This allows resolution of conflicts at any point in the future on any replica. CRDTs so far have mostly captured operations on sets, counters, last-writer wins registers (LWWR), connected graphs and domain-specific datatypes e.g. for text editing [8]. None of these datatypes allows to consistently order distributed writes. Other CRDTs nonethe-

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3https://github.com/presslabs/gitfs
4https://git-annex.branchable.com/
5http://basho.com/tag/crdt/
6https://github.com/soundcloud/roshi
less have benefits compared to our CDVCS datatype, because they cause less overhead on replication and do not require conflict resolution with reduced availability on application level, provided concurrency of the datatype operations is acceptable. We hence generalized our replication with a CRDT interface and reformulated our datatype together with an OR-set in terms of this interface.

Similarly to CRDTs, cloud datatypes [2] build on commutativity of update operations. The design still happens from a cloud operator’s perspective, though, as their flush operation allows explicit synchronisation with some central view on the data on a cloud server. All their non-synchronized datatypes can be implemented with commutative CRDTs.

Close to our work are versionable, branchable and mergeable datatypes [7]. This work models datatypes with an object-oriented approach as a composition of CRDT-like commutative datatype primitives (e.g. sets). To resolve conflicts, each application needs to instantiate custom datatypes which resolve conflicts at the application level. Therefore, the code for conflict resolution has to be provided consistently to each peer participating in replication. Having general data types and compositions thereof in contrast allows us to replicate without knowledge of the application and to upgrade the replication software of the CRDTs more gradually, independent of application release cycles. It also means that all peers can participate in the replication no matter whether they have been assigned to an application or not.

swarm.js 7 is the closest to our work. It employs op-based CRDTs for client replication and runs in the browser, allowing efficient offline applications. In contrast, replikativ uses a dual representation of a CRDT, state-based in-memory and op-based on runtime during operations. This in-memory representation allows to store an efficient local compression of the operation history which is straightforward to implement for each CRDT and does not leak into the replication of operations. Further, swarm.js has not been designed as an open replication system. It uses a spanning tree to minimize the replication latency of ops, while we build on a gossip-like protocol as building self-stabilizing spanning trees over the internet is still an open area of research [3]. Our peer-protocol can be easily extended by middleware systems concerning just a single connection without dependencies on the code base. To our knowledge, swarm.js lacks a mechanism to exchange external values, most importantly (large) binary values. Our system uses referenced values by their platform independent hash, so datatypes only need to carry 32 bytes for every transaction. The referenced values need to be transmitted as well, of course, but can be structurally shared between datatypes and even commits.

3. APPLICATION: SHARED CALENDAR

replikativ provides essential middleware functionality for implementing distributed applications, covering client communication, durable data storage, and consistency management. Let us sketch how application developers can employ this functionality.

As a basic example, consider a calendar application where people store their appointments and synchronize them with others. In the context of this paper, we simplify the calendar application by tracking only titles of appointments and their time. Each appointment is tracked as a branch. Let us assume that Alice and Bob want to use a shared calendar to synchronize on a lunch appointment, alongside the otherwise private appointment branches as shown in Figure 1. Alice has to work at 2 pm, therefore she wants to eat lunch earlier at 1 pm. Bob has soccer practice at 3 pm, so he prefers lunch actually later at 2 pm. Once their clients are connected, both transmit their concurrent operations to each other. This causes a conflict because they have set a different time for their lunch. The application now notifies Alice and Bob to resolve the conflict. Alice merges both commits following a user-moderated consistency scenario section 5.3. The operation is then transmitted to Bob’s client and also applied there.

4. CDVCS DATATYPE

We compose a CRDT satisfying the requirements from Footnote 1 by implementing a DVCS with the primitives available from CRDTs. Our consistency requirement for an ACID transaction log demands a sequential history. In DVCS, this is captured by an add-only, monotonic DAG of commits which represent identities, i.e. values changing in time. The graph is monotonically growing and can be readily implemented as a CRDT [8]. To track the identities in the branch, we need to point to their heads in the graph.

In a downstream update operation to a branch with head a, e.g. one reflecting a commit b, the branch heads are now {a, b}. This is resolved in a DVCS by a lowest common ancestor search (LCA). Whenever we want to resolve a branch value, i.e. its history, we need to remove all stale ancestors and either have only one head or a conflict of multiple ones. We therefore remove stale ancestors in the set of heads on downstream operations, so we do not need to use a CRDT for the branch heads.

Combining the DAG, the sets and LCA completes our CRDT which we refer to as confluent DVCS or CDVCS.

Correctness.

To show that CDVCS behaves properly as a CRDT, we have to show that all operations satisfy the invariants of its metadata. In particular the graph might never lose nodes or edges and always grow according to the operation. All branch heads must always point to leaves of the commit graph and might only be removed if they are non-leaves (ancestors) of one of the others. For (operation-based) CRDTs, operations are split in upstream and downstream operations, where the former ones are applied at the local state of a replica, leaving the state unmodified, and the latter ones are manipulating the state and are used to propagate the changes also to the other replicas.

CRDT specification.

The correctness of CDVCS heavily relies on LCA which is used in a typical DVCS to resolve conflicts. We use an online LCA version which returns a set for common ancestors and the subgraphs traversed to reach the ancestor(s) from each commit. We cover the following operations, which we refer to by visited:

- commithistory: Linearizes the history back to the root from some commit, e.g. head of a branch, and loads all commit-values from memory as can be seen in Figure 2 on the right. It can be used to calculate

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7https://github.com/gritzko/swarm
8http://swarmjs.github.io/articles/2of5/
Figure 1: States and operations side-by-side representing dynamic processes of an example calendar application where the CDVCS tracks the complete application state. Each CDVCS has multiple branches that describe an appointment. Both instances of the CDVCSs have a branch which is shared and one which is private to each CDVCS. Conflicts can only arise in shared branches.

Figure 2: The state of two repositories illustrating typical operations. Commits are represented as circles with black colored head commits. Both repositories have '1' as initial commit, one shared and one private branch each. While Branch2 exists before Branch3, Repository2 pulls all missing commits into a new branch from Repository1. Furthermore, by having two branch-heads in '4' and '5', a merge into '6' is applied based on some consistency scenario. The grey nodes represent the commit history from the head node '10' of Branch4 up to the root.

- **commit**: Commits a new value to a branch. Since it just carries the edge and node added to the commit graph and the single new branch head in a set, the downstream operation will ensure that it is applied correctly.
- **branch**: Creates a new branch given a parent. This operation forks off new branches directly at a commit without creating a new one. Since it just adds a new branch-id and initial head, the branch is correctly setup.
- **pull**: Pulling adds all missing parent commits to the graph and adds the selected head into a set for the branch as can be seen in Figure 2.
- **merge**: Merge resolves a conflict between multiple branch heads $H'$ by adding a new commit with $H'$ as parents as can be seen in Figure 2 or Figure 1.
- **downstream** All operations only carry additions to the graph and sets of branch heads. We just have to apply all additions to the graph and merge the sets of heads. Since LCA properly detects all ancestral heads, we can calculate the currently active heads safely by pairwise comparison. A special case is the initial full-state replication. Here the unknown part of the remote state is fetched and added to the own state by following the same procedure, which is also correct in this case. All dependencies are always fetched before atomic application, so the peer is in a self-consistent state and can act as a data provider for other peers if it is used with full replication.
payload graph $C$, set $H ← C$: commit graph; $H$: branch heads
initial $\{r → [], \{r\}$
query $\text{commitHistory} (\text{graph } C, \text{commit } c) : L$
$S ← \text{emptyStack}()$
let $L = \text{topologicalSort}(C, [], S, \{\})$
update $\text{commit} (\text{commit } c)$
prepare ($e$)
let $\hat{C} = c → [p]$
let $\hat{H} = \{c\}$
effect ($\hat{C}, \hat{H}$)
$C ← C ∪ \hat{C}$
$H ← \text{removeAncestors}(H ∪ \hat{H})$
update $\text{pull} (\text{graph } C, \text{commit } c)$
prepare ($e$)
if $\#H = 1$ then
let $h = H padre()$
let $\hat{C} = \text{lea}(C, h, C, c).\text{visited}_c$
let $\hat{H} = \{c\}$
effect ($\hat{C}, \hat{H}$)
$C ← C ∪ \hat{C}$
$H ← \text{removeAncestors}(H ∪ \hat{H})$
update $\text{mergeBranches} (\text{vector of commits } H')$
prepare ($e$)
let $\hat{C} = e → H'$
let $\hat{H} = \{c\}$
effect ($\hat{C}, \hat{H}$)
$C ← C ∪ \hat{C}$
$H ← \text{removeAncestors}(H ∪ \hat{H})$
merge ($S$)
$\hat{C} ← C ∪ SC$
$H ← \text{removeAncestors}(H, S, H)$

Figure 3: CDVCS: A DVCS-like datatype. Here we just model one branch to unclutter notation. Every DVCS with multiple branches can be represented by multiple clones of the same DVCS. [...] denotes a vector of elements.

5. CONSISTENCY SCENARIOS

Since the major difference of CDVCS compared to commutative datatypes is the decoupled value-level conflict resolution, we now want to explore how this can be used to gain different trade-offs between consistency and availability in applications.

An important problem in distributed application design are the changing scalability demands during the life cycle of an application. For initial prototypes, no coordination or user moderated coordination (section 5.3) might be sufficient. Once the state space and workload increases, data moderated (section 5.4) splits into commutative CRDTs and CDVCSs can render the application both correct and efficient with explicit semantics for the developer to monitor and optimize the data synchronization. A relational query engine can be filled continuously with this mix of datatypes decoupling the application level code from the CRDTs. If the need for strong consistency arises, only some coordination mechanism has to be added, while our replication protocol still takes care of everything else. We pursue this strategy in our social network demo application topiq\(^9\) with

\(^9\)https://topiq.es

5.1 Strong consistency

As an example for strong consistency, we consider the transaction log of a typical ACID relational database as is modelled in topiq. Such a transaction log cannot be modeled by traditional CRDTs in a system with distributed writes, since arbitrary merges of non-commutative operations break consistency.

5.2 Single writer

In a traditional database like Datomic\(^11\) represented by a linear transaction log, strong consistency can be modeled by having a single writer with a single notion of time serializing the access to the transaction log. CDVCS naturally covers this application case as a baseline without conflict resolution.

Interesting new choices are possible when different peers commit to some branch creating different branch heads and the decoupled conflict resolution comes into play. In these cases, conflicts can occur, but they might still be resolvable due to application level constraints or outside knowledge.

5.3 User moderated consistency

In our replication system, each user can commit to the same CDVCS on different peers at the same time only affecting her own consistency. The user takes the position of the central agent providing consistency. Consider as an example a private addressbook application. In this case, we can optimistically commit new entries on all peers (i.e. mobile phone, tablet, notebook), but in case where the user edits the same entry on an offline and later on an online replica, a conflict will pop up once the offline replica goes back online. Automatic resolution is infeasible because the integrity of the entry without data loss can be best be provided by the user. Since these events are rare, user-driven conflict resolution is the best choice and can be implemented by the application appropriately in a completely decentralized fashion.

5.4 Data moderated consistency

Similar to the hotel booking scenario in [7], we can allow to book a room optimistically and then have one DVCS in the system updated strongly consistently on a peer which selectively pulls and merges in all changes where no overbooking occurs. It provides a globally consistent state and actively moves the datatype towards convergence. The advantage of the CDVCS datatype is that this decision can be done locally on one peer, independent of the replication, while in [7] the central peer needs to be known and actively replicated to. Since the decision happens again in a controlled, strongly consistent environment, it can happen supervisely and arbitrarily complex decision functions can be executed atomically. Assume for example that the preferences of a user in a different CRDT or database allow rebookings rooms in a comparable hotel nearby. In this scenario, the pulling operation can decide to apply further transactions on the database to book rooms in another hotel depending on information distributed elsewhere instead of just rejecting the transaction. Furthermore, part of this information could be privileged and outside of the replication system, making it
impossible in a system of open replication like ours to automatically merge values on every peer. Conflicts in term of CDVCS might in many cases still be resolvable by applying domain knowledge.

6. EVALUATION

We have continuously evaluated replikativ with topiq on a diverse set of mobile and desktop browsers and found that the replication behaves robustly despite the occasional inefficiencies occurring during development. A second application\(^\text{12}\) is the management of data from experiments run on a scientific simulation cluster with the help of Datomic. In this case, the datatype is used manually in an interactive REPL to track experiments including results of large binary blobs, which is infeasible with git or even a centralized Datomic alone.

Our work so far has mostly been focused on finding the proper interfaces and levels of abstraction for replikativ to behave correctly and reliably and allow straightforward optimized extension to new CRDTs. But since performance and scaling of any distributed system are critical and tradeoffs need to be known, we have conducted some optimizations and run first benchmarks as you can see in Figure 4. Most importantly commit times are hold almost constant by application of Merkle-tree like partitions of the metadata.

7. CONCLUSION

Together with our new datatype replikativ is a promising platform to provide efficient replication as a service (RaaS). Importantly, the available mix of datatypes together with replikativ allows to balance different consistency vs. availability trade-offs depending on the application semantics and scale. While we are now able to satisfy our initial requirements, we are working on extended prototypes to benchmark and verify our approach together with the open source community. As an open and global network of replication, we plan to provide support for application developers who do not want to care about scaling of their backend either publicly or in private replication networks. Already now, the development of the demo applications is significantly easier than having a dedicated backend, and feels more like management of local state in native applications than the typical web development architectures. Cross-platform data semantics are achievable. Since we explicitly build on the research around CRDTs, our datatype semantics are transparent to the developer. Through the implementation of new and modified CRDTs we will be able to adapt the replication system to new needs while keeping old data and applications available.

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