Sorbonne Université

Code offloading from the EDGE

Rapport de stage

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1 Introduction

An application that relies on a geo-replicated database must process a large volume of data. To provide low latency answers to a client, the application stores a subset of those data on the client device. This allows a client to execute transactions without contacting a far away data centre. We recall that a transaction is an atomic unit that encapsulates read and write operations. The main property of a transaction is that all the operations it encapsulates must be performed or none of them. Caching data on the client device provides better performance for transactions with few reads and writes. But such an application also needs more complex transaction that can be demanding in computation resources. Processing this kind of transaction in the client device is problematic if the device has low-resources, like a smartphone for example.

Consider a social media application based on a geo-replicated database. To compute the homepage of a user, the application performs a read transaction to collect all the relevant post, then another transaction to collect all the comments on each post, another transaction to get info about the users who post a comment, etc. This implies many round trip between the application and the data centre. Another issue is the useless retrieval of a large amounts of data. For example, to list all the users in a certain region, we will have to scan the whole database and filter at the client device. A certain amount of data was pushed unnecessarily to the client device since only a subset will be kept after the filtering.

The work of this internship is built upon the geo-replicated database Antidote. The goal is to implement a module, placed on an Antidote data centre, which adds the capability to upload a procedure on a data centre. A client could therefore call this procedure remotely instead of executing it locally. The data centre executes this job, but the result of this execution needs to leave the client in a state equivalent to that obtained in a client side execution. Indeed, a client device in our system hosts EdgeAnt, a cache that contains a partial replica of the database and is able to maintain system-wide consistency guarantees. When we decide to execute a piece of code in a data centre rather than in a client device, we need to leave the EdgeAnt cache in a consistent state.

In this report, we present the state of the art of consistency in database systems, then we describe the architecture of the system in which we implemented our solution, and finally our contribution.

2 State of the art

Before moving on to the technical part of our internship, we needed to acquire the necessary knowledge to understand the system in which to integrate our solution. In particular, we needed to read about consistency on replicated databases and transaction model. We present in this section, a resume of what we learned during this internship.

2.1 Consistency in geo-replicated databases

The geo-replication of data, provided by modern database systems, is a crucial feature in a context where mobile or web applications need to handle a significantly high volume of requests, since it makes the system more scalable by reducing the possibility for bottlenecks to be formed. It also reduces the latency perceived by the clients by routing their requests to the closest data centre. Finally, the system is more fault tolerant as it can continue to work even if one or more data centres are unavailable. One of the challenges of building such systems is to maintain efficiently the consistency over the replicas. Consistency in this context means that we want to minimize divergence between the replicas. We briefly present in this section some level of consistency in distributed databases.

2.1.1 Strong consistency

Also called serializability, it guarantees that transactions, ran in parallel by different replicas, are observed in the same order by all replicas. This total order gives the impression to the users that transactions are executed sequentially. It is a comfortable model for developers, first because it prevents any ordering anomaly of the operations, and secondly because it is managed at the database level, so developers do not need to worry about consistency problems while coding their applications.

The replicas need to execute a consensus protocol to establish a total order of the operations. The problem is we reintroduce a point of contention by performing a consensus for each operation. Furthermore, consensus algorithms require a majority of agents of the system to be alive, so we also decrease the resilience to failure.

2.1.2 Eventual Consistency

In this model of consistency, the system can diverge for a unbounded time, after which the replicas will reach an equivalent state. In practice, every replica can immediately process local updates, and then propagate those operations asynchronously to the other replicas. It is called lazy replication. Formally, every update applied by a correct replica will be applied by all the correct replicas of the system, which is the property of eventual delivery, and every replica that applied the same update will eventually reach an equivalent state, which is the property of eventual convergence. This equivalent state can be reached after a possibly long and complex conflict arbitration process, if during the propagation of updates, we realise that some invariants are globally not respected. In this process, a replica can rollback to a state preceding the conflict, then engage in a consensus with the other replicas to take a global decision on each update (their order, if they are applied or dropped).

This model provides a more available system by putting the point of contention in the background. However, it still relies on consensus, and the conflict arbitration is more complex than the simple total order needed in strong consistency, which operates at the database level, while invariant violation in eventual consistency must be managed by the developer at the application level.

2.1.3 Strong Eventual Consistency

Strong Eventual Consistency is a subset of Eventual Consistency and aims to provide lazy replication without any coordination between the replicas. In this model we still have the property of eventual delivery, but the convergence property changes. We define that every replica that applied the same update has the same state. The convergence is immediate once every update is applied. This property is ensured by defining a set of rules to handle every conflict deterministically. One simple way to obtain this property is to adopt the Last-Writer-Wins strategy. This strategy can resolve conflict between two updates by keeping the most recent one. It a very simple strategy, but the trade-off is that we can lose (a lot) of updates. Antidote is a geo-replicated database that provides Strong Eventual Consistency by using distributed datatype called Conflict-free Replicated DataType (CRDT) [1].

2.2 CRDT

Conflict-free replicated datatypes (CRDTs) are a family of data structures that guarantee convergence of concurrent updates. A CRDT abstracts a high-level structure like a set, a map or a counter and provides an interface for each type: add, remove for a set; increment, decrement for a counter; etc... The implementation of those types can be state-based or op-based. The key difference between those two families is the replication method.

2.2.1 State-based CRDT or Convergent Replicated Data Type (CvRDT)

After an update on a state-based CRDT, its state is propagated to the other replicas. This means that a replica needs to be able to merge two different states of an object. State-based CRDTs use a mathematical structure called a semilattice to ensure that two states can be merged correctly, while conserving as much as possible the effects of concurrent updates. A semilattice is a set with a partial order $\leq$ equipped with a least upper bound (LUB) $\sqcup$ function. LUB is defined as such:

Definition. *For a given domain of definition X with a partial order $\leq$ and $m, x, y \in X$, $m = x \sqcup y$ is a LUB under $\leq$ iff $x \leq m$ and $y \leq m$ and $\nexists\ m' \leq m$ such that $x \leq m'$ and $y \leq m'$*

What makes this structure ideal for our use case is the following property of $\sqcup$:

- $\sqcup$ is commutative and associative, so an updated state can be received on different orders by all replicas. If they all receive it, they will converge.

- $\sqcup$ is idempotent: $x \sqcup x = x$. This property allows a replica to receive and apply the same state multiple times, and still converge to the same state as all replicas.

To these properties, CvRDTs add that every update monotonically advances upwards according to $\leq$, which means that after an update the state is greater or equal the state before.

A simple example of a CvRDT is a grow-only counter. The state of the object is a vector with one entry per replica. Each replica increments its own entry. To read the value of the counter, we make the sum of all the entries. When a replica received a remote state, it creates a new state by applying the max function on all the entries. The max function returns a LUB for this type.

The advantage of this structure is that we can have weak guarantees on the communication channels between the replicas, thanks to the properties of $\sqcup$. Messages may be lost, received out of order, or multiple times, if the new state reaches all replicas, they will converge. The main disadvantage is that the state of an object can grow to be very large with time, so sending the entire state will tend to be inefficient.

2.2.2 Op-based CRDT or Commutative Replicated Data Type (CmRDT)

After an update on an op-based CRDT, only the update is propagated to the other replicas. This is less consuming in bandwidth, but is more complex. Compared to the state-based approach, an update received multiple times or in an incorrect order will bring inconsistency. CmRDTs need a reliable broadcast that delivers updates on every replica in causal order. Only concurrent operations need to commute.

2.3 Transaction protocols

To provide a high throughput—a high number of transactions treated in some unit of time—databases must be able to execute transactions concurrently. Modern databases rely on multithreading and on the distribution of work between several server machines. They need complex concurrency control mechanism to maintain performance and consistency. Choosing between the different transaction protocols existing is making a choice on where we want to place ourselves in the trade-off between performance and consistency. In the previous section we described informally that some protocol does not scale well when consistency is maintained between several replicas. Here, we describe different transaction protocols at different points of the performance-consistency spectrum. Snapshot Isolation is strongly consistent, but weaker than Serializability. Parallel Snapshot Isolation is a relaxation of Snapshot Isolation that allows lazy replication, Transactional Causal Consistency is made for strong eventual consistency, and is the transaction model used by Antidote.

2.3.1 Snapshot Isolation

Snapshot Isolation (SI) [2] is a form of multi-version concurrency control. This model of concurrency control relies on keeping multiple versions of each object. Transactions can execute optimistically under the assumption that concurrency issues will occur rarely, SI checks for them during commit.

In snapshot isolation a transaction executes on a logical snapshot of the database. A transaction observes the state of the database as when the transaction started. If the transaction updates a data item, it does not overwrite the object, but creates a new version. The snapshot is commonly a timestamp, and every version of a data item is paired with the timestamp of the commit that created it. When a transaction starts, all the versions with a commit timestamp lower than the transaction's start timestamp are visible. Versions written by a concurrent transaction are not visible: two transactions T_1 and T_2 are concurrent if T_1 has its commit timestamp between the start and commit timestamps of T_2. This model ensures that transactions access a consistent view of the databases and improves concurrency by avoiding to use of locks to synchronise transactions, in particular read-only transactions are not blocked by write transactions. Write-write conflicts, which arise when two concurrent transactions update the same data, are avoided during commit; only the first committer succeeds. SI does not provide serializability as it allows the anomaly called "short fork" or write-skew. This anomaly occurs when two concurrent transactions read a key updated by the other. Here is a sequence executed by two concurrent transactions T_1 and T_2, where the write-skew anomaly can occur:

$$Init : a = b = 1; \tag{1}$$

$$T_1 : write(a) = 2;\ read(b) = 1 \tag{2}$$

$$T_2 : write(b) = 2;\ read(a) = 1 \tag{3}$$

The result of this concurrent execution is not possible under sequential execution, yet it is allowed by SI, because the two transactions do not update the same data.

Despite being weaker that serializability, SI is still on the strongly consistent side of the spectrum. SI requires that replicas observe the same commit ordering. A total order ensured only on the write transactions improves performance compared to serializability, at the cost of the anomaly presented. However, it requires heavy coordination between replicas, preventing a lazy replication approach.

2.3.2 Parallel Snapshot Isolation

Some geo-replicated key-value stores that provide eventual consistency (EC) do not provide transactions, like the very popular Dynamo [3] for example. Parallel Snapshot Isolation (PSI) is a relaxation of SI made to be compatible with eventual consistency [4]. PSI supports interactive transactions (transactions with both reads and writes), and can propagate updates asynchronously, but can not always execute transactions without synchronization between the replicas because it forbids write-write conflicts.

In PSI, data centres can have different commit orderings. Updates are propagated to remote sites according to causal consistency. Causal consistency is a model that maintains the "happened-before" (noted $\rightarrow$) relationships between transactions in all replicas. This relationship is defined as follows:

- If the transactions T_1 and T_2 execute on the same replica, $T_1 \rightarrow T_2$ if T_1 committed before T_2 started.
- if T_1 and T_2 execute on different data centres, $T_1 \rightarrow T_2$ if T_1 is received and committed by the replica that starts T_2, before T_2 starts.

To maintain causal consistency, a snapshot in PSI is represented by a vector with one entry per replica. One of the entries is the local timestamp of the data centre. The others indicate how many transactions from each remote data centre are reflected in this snapshot.

For example, in a site with two or more replicas, Site 1 executes sequentially the transactions T_1 and T_2, and Site 2 executes T_3 and T_4. After propagation of the updates, every replica must apply T_1 and T_2 in this order and similarly for T_3 and T_4. However, replicas can have either T_1, T_2, T_3, T_4 or T_3, T_4, T_1, T_2, indeed a total order is not required for transactions that are not causally related. This relaxation of consistency enables to propagate updates asynchronously, as there is no need for synchronization to define a total order. It also enables the "long fork" anomaly, where it is possible that two transactions T_1 and T_2 commit on different replicas, writing to different data items, and then two other transactions T_3 and T_4 that start subsequently, where one sees the effects of T_1 but not T_2, and the other sees the effects of T_2 but not T_1. Example:

$$Init : a = b = 0; \tag{1}$$
$$Replica\ 1 : \quad T_1 : write(a) = 1;\ T_2 : read(a) = 1, read(b) = 0; \tag{2}$$
$$Replica\ 2 : \quad T_3 : write(b) = 1;\ T_4 : read(a) = 0, read(b) = 1; \tag{3}$$

The two branches converge once updates are propagated, but we can see again that consistency had to be sacrificed to raise performance.

PSI does not completely reach the objective of eventual consistency, where local updates do not need synchronization with other replicas. Some synchronization is still necessary to avoid write-write conflicts. To minimize synchronization, PSI defines *preferred sites*. It comes from the idea that users will have a set of objects that will only be accessed by them, on only one site locally close to them. Each object is assigned a preferred site. When a transaction updates an object on its preferred site, it can commit with a *fast commit* protocol with no synchronization. When a transaction updates an object on a data centre other than the object's preferred site, the transaction needs to executes a two-phase commit protocol with the preferred site of the object to be sure that another transaction does not already update this object.

2.3.3 Transactional Causal Consistency

There are research works on highly available transaction — transactions with no foreground coordination between the replicas — that executes on causally consistent snapshot [5, 6]. Those works allow the creation of "convergent fork", where the same objects can be updated concurrently on different replicas, to be reconciled later. Causal consistency added to convergent fork constitutes the consistency model called "Causal+ consistency". The limits of those works are that they do not support interactive transactions, and convergence is achieved using last-writer-wins (LWW).

Cure is an answer to those limitations [7]. It introduces a novel consistency model called "Transactional Causal Consistency", which supports highly available interactive transactions, causal consistency and convergent fork using operation-based CRDTs. Cure had been developed with partitioned and replicated databases in mind. This is the transactional model used in Antidote.

A partitioned or sharded database aims to improve the concurrency and therefore the performance of the system, by partitioning the key space over several server machines. Those databases use a consistent hashing mechanism to determine which key is managed by which server. Distribution of the data means distribution of the processing, and therefore better availability. For example, this is the case of Antidote, where each data centre manages a full replica of the data. One data centre is composed of several servers, each managing a subset of the key space. A partitioned database has a higher throughput than a centralized system, but are more complex to reason with, especially if we want to maintain consistency. Two problems not present in [4] for example, which implements PSI on a centralized data centre, had to be considered while specifying Cure to be correct in term of consistency. The first problem is the attribution of timestamp to create a snapshot in a decentralized manner (a centralize solution is possible but would create a bottlenecks). The second problem is determining that a remote update can be made visible, that is to say to ensure that all the partitions received its causal dependencies.

Generate timestamps in a decentralized system.
Cure takes inspiration from ClockSI [8], to generate timestamps in a decentralized manner using physical clock. ClockSI is a distributed protocol to implement Snapshot Isolation on partitioned databases. In SI, we recall that a write transaction creates a new snapshot when it commits. Snapshots are represented by monotonically increasing timestamps. Those timestamps can just be a counter increased atomically in a centralized system. In a partitioned system, we could have one server dedicated to provide timestamp to partitions, but this solution would lower transaction throughput by forming a bottleneck. ClockSI uses loosely synchronized clocks to create snapshots. Hardware clocks of each server are

synchronized by a clock synchronization protocol like Network Time Protocol. Each server can generate a timestamp locally without any communication. We know that to rely on physical clock to synchronize different server machines can be challenging because of clock skew. ClockSI proposes two solutions, each on a side of a trade-off between decreased throughput or reading stale data. The first solution chooses to decrease performance. A transaction takes its start timestamp from the partition which received the request. If it accesses keys from other partition, the transaction is sent to those partitions. A transaction must see every version committed before its start snapshot. If the clock of a partition accessed by a transaction is behind the transaction's start timestamp t, the partition can not execute the transaction because the snapshot with timestamp t is not yet available. To solve this problem, the partition waits until its clock catches up. The other solution proposes to assign a start timestamp slightly smaller than the local clock value, to reduce the probability and duration that an operation needs to be delayed. This solution results in transactions reading from an older snapshot and therefore increase the chance to read stale data. Cure uses the first solution.

Make remote updates visible.
Transactions originating at a data centre are immediately visible to the DC's clients when they commit, as their causal dependencies are automatically satisfied. Updates propagated from remote DCs can be made visible only if all their causal dependencies are also received. We explain in this section the protocol used by Cure to propagate updates to remote DCs, and to ensure that it received all its dependencies before including them in a snapshot. The propagation of updates is made at the partition level. An example of execution we want to avoid: a transaction on DC_1 updates object o_1 on partition P_1 and object o_2 on partition P_2, P_1 and P_2 propagates their updates to their sibling partitions P_1 and P_2 on DC_2 (sibling partition from different data centres handle the same key space). If a transaction starting on DC_2 reads the new version of o_1 on P_1 but can not read the new version of o_2 because P_2 did not receive it yet, then we violate transaction's atomicity property. Causal consistency can be violated the same way, if we read a data item from a partition, while its dependencies on other partitions have not been received.

To prevent those errors, partitions of a DC periodically communicate to compute a Globally Stable Snapshot (GSS). This snapshot represents a view of the database that is available at every partition. To compute this GSS, each partition maintains a version vector sized as the number of the DCs. One of the entries is the local timestamp of the partition. The others represent how many updates from sibling partitions have been received. Partitions periodically exchange their vectors and compute the GSS as the aggregate minimum of those vectors. For example, if a partition P_1 has a version vector $[5, 4, 3]$, and receive $[3, 2, 1]$ and $[5, 3, 2]$ from P_2 and P_3, P_1 will compute the GSS $[\perp, 2, 1]$. The entry for the local DC is $\perp$ because, as we said earlier, every locally committed transaction is seen immediately, GSS exists only to read remote updates safely. The local entry of the partition vectors is used by transaction when they want to read at a specific time on the local DC and by remote partitions to compute their GSS. Since the process is asynchronous, partitions can have different GSS at a given time, but it does not impact correctness. To ensure that the GSS increases, sibling partitions periodically send each other heartbeat when they do not have updates to propagate. Reading from a globally stable snapshot ensures consistency but can result to reading stale data. The amount of time between the moment a transaction is committed at its originating DC, and the time at the receiving DC when the updates are made visible, is dependent of the latency to the originating DC and the latency between the server machine within a DC.

In conclusion, we present on this table from [7], the different transaction protocols discussed from the stronger to the weaker in term of consistency.

Properties	Serializability	SI	PSI	Cure	CC+	EC
Transactions	yes	yes	yes	yes	read-only write-only	no
Short fork anomaly	✗	✓	✓	✓	✓	✓
Long fork anomaly	✗	✗	✓	✓	✓	✓
Convergent fork anomaly	✗	✗	✗	✓	✓	✓
convergence	-	-	-	CRDT	LWW	LWW

Table 1: Transaction protocols range from stronger to weaker consistency model (✗: disallowed).

2.4 Edge computing

We explained how cloud-scale services improve availability and latency by geo-replicating data in several data centres across the world. We also presented the possibilities of placement in the consistency-availability trade-off. This field is widely explored by industry and academia. One of the main challenges of those services nowadays is to push geo-replication to the Edge. Indeed, the closest data centre is often still too far away for an optimal experience. To avoid the round-trips to a data centre, client side applications, like web or mobile applications, need to store and update data locally to remain responsive at all times. It may not be a difficult problem for eventually consistent databases with no consistency guarantees. But developers of client side applications based on geo-replicated cloud-services offering strong consistency guarantees, will face problems to maintain those guarantees system-wide.

Small devices at the Edge have less storage capability than a data centre. Therefore, they can not support the replication protocols used between data centres. We can only provide partial replication to the Edge. Maintaining consistency with only a partial view of the database is a novel research topic. During this internship, we studied Swiftcloud [9] a novel approach to create a causally-consistent cache in the client side. It provides causal consistency system-wide and fault-tolerance with light metadata. Our contribution is integrated to EdgeAnt, an implementation of Swiftcloud, which will be described later.

3 System specification

In this section, we describe the architecture of Antidote, a geo-replicated Key-Value store. Then, we talk about EdgeAnt a causally consistent cache for Antidote. It is placed on the client device, and in addition to a robust caching service, it provides fault-tolerance properties and the capability to execute transactions locally without being connected to a data centre. Finally, we present our contribution, a module placed within a data centre able to execute a procedure on the server side on behalf of the EdgeAnt client and then update the EdgeAnt cache, leaving it in a correct state.

3.1 Antidote

Antidote is a Key-CRDT store, providing the strongest consistency model compatible with high availability. Antidote is composed of a set of interconnected data centres (DCs) called Antidote nodes, each managing a full replica of the database and geo-located across the globe. Antidote provides linear scalability; one can easily connect a new Antidote node to the system to improve availability and throughput. Within a DC the key space is partitioned using a persistent hashing mechanism, each partition being managed by an entity called virtual node (vnode). Vnodes are processes fairly distributed on all the machines of the DC, there is a server machine by partition. Antidote can execute reads and updates atomically in parallel across these partitions, achieving better throughput than a single machine system. Reads and updates are encapsulated in a transaction for atomic execution. Antidote's transaction provides causal consistency, freeing developers from worrying about ordering anomalies. Antidote uses Cure, a highly scalable protocol, to replicate updates among DCs and maintain system-wide consistency. The data stored by Antidote are op-based CRDTs, a data type that allows Antidote to perform fully asynchronous replication. More precisely, Antidote stores only CRDTs operations. It computes the complete state of a version by applying each operation one after the other during a read request.
For each partition the following processes are instantiated:

Transaction Manager: This process is the client interface. It receives and executes client requests and hides the fact that a transaction can be divided between several servers. It executes the transaction protocol of Cure described earlier permitting to execute transactions on causally consistent snapshot, even when they access multiple partitions. If a write transaction updates different partitions, the process proceeds to a two-phase commit protocol with all the partitions involved.

Materializer: We said that Antidote used op-based CRDTs, so necessarily it needs a process that can assemble all the updates belonging to a snapshot to create the state of an object. This process is the Materializer. With a pair (key, snapshot) given by the Transaction Manager during a read operation, the Materializer requests the persistent storage layer to get all the updates made on that key and belonging to this snapshot. Then, it uses the CRDT library to merge those updates and return an object. To avoid this costly process, the Materializer has an in-memory cache, that contains materialized objects.

Log: The logs are the persistent storage of the system. They are for the moment very basic; every update operation is stored in the log sequentially, so the access to operations belonging to a snapshot done by a materializer is slow. Furthermore, there is no checkpointing mechanism yet, so a log can run out of space.

InterDC Replication: Those processes have the responsibility to broadcast every update locally committed to the other DCs of the system. This is performed asynchronously, following the replication protocol of Cure described.
The figure 1 illustrates this architecture.

In the current state of the system, an application backed up by Antidote can communicate with a DC thanks to an API available in Java and Erlang, based on protocol buffers, a language-neutral, platform-neutral mechanism for serializing structured data. The API connects to a DC with a socket and sends serialized operation to the server.

3.2 EdgeAnt

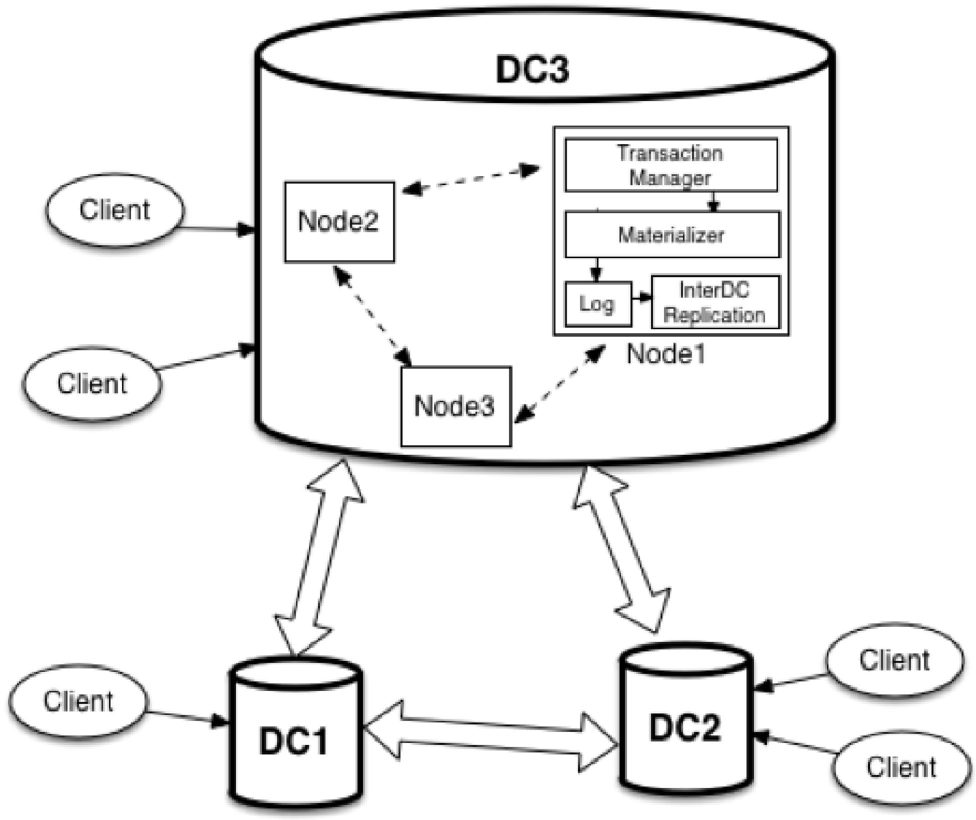
A user can communicate with Antidote through an API that provides a simple way to develop applications based on Antidote, but is very basic, providing a way to connect to a DC and send transactions. A developer who desires to write an application based on Antidote will have to build important functionalities of such system, like a cache, handler of network failure, etc...

EdgeAnt is a module, that simplifies the creation of application using Antidote. It implements the SwiftCloud approach [9] to extend geo-replication to the client machine, pushing consistency, convergence and availability guarantees to the client cache.

First it provides a causally consistent subscription service: applications can subscribe to a set of keys, its interest set, and every time an update occurs on one of the keys, the data centre notifies the client with the new value. This way, causal consistency between client cache and updates from other clients is maintained by the data centre, that we can trust to send only causally consistent updates.

EdgeAnt can also dynamically switch from a crashed DC to an available one. Finally, it has the capability to use the data present in the cache to repair a failed DC. Applications interact exclusively with EdgeAnt in a very transparent way, because it exposes the same protocol buffer interface as Antidote. EdgeAnt forward requests to the Antidote server, after passing them through two components: its state cache and log cache.

Figure 1: Architecture of an Antidote system with three DC.



State cache: The state cache stores the state of the objects from the user's interest set and every read is performed through this cache. At initialisation, the cache is filled with the state of all the keys in the interest set. This projection of the data centre's state into the interest set is necessarily causally consistent. Afterwards, the state of the client can change because of internal updates or external updates received from a DC. Internal updates made on a causally consistent state maintains causal consistency. External updates coming from other users are pushed by the DC when it makes them visible. We can trust the DC to send causally consistent updates, so the consistency is maintained system-wide.

If a read is made on a key not present in the interest set, this key is added in the set. If there is a cache miss, all the interest set is synced with the Antidote node. The reason to sync all the interest set and not just read the missing object is that we want to guarantee causal consistency at every instant in the cache. If we only read one object, we could miss some causal dependency.

Log cache: The log cache stores every local update. Its goal is to permit the user to make fast writes by avoiding round-trip with the Antidote node every time. The principle is that write operations update the state cache, and then are buffered in the log cache. Later, a background thread sends asynchronously those updates to the node. Once an operation has been successfully sent to the DC, it is evicted from the cache. This mechanism makes writes faster, but also permits offline updates as it is not necessary to be connected to a node to update the cache. The application can therefore work even in case of network partition or failed node. The process of an update is as follows: first there is a check to see if the object is present in the state cache. If it is the case, the cache is updated, otherwise the state cache is synced with the DC, like for a read, and then the cache is updated.

Those two caches are implemented with a classical LRU algorithm. If the state cache is full, then the least recently used object is evicted from the cache, at the condition that every update on this object on the log cache is sent to the DC. If the log cache is full, either because the pace of the writes is way superior than the propagation's speed of the updates to the DC or because the user is making a lot of write while offline, then the user can not submit any write until the cache flushes its updates.

Metadata: EdgeAnt uses a lightweight metadata design to ensure causal consistency and at-most-once delivery. Each update is initially associated with a client-assigned timestamp and a version vector. The client-assigned timestamp is a pair (clientID, sequence number). ClientID is a unique identifier provided by the DC when the client starts a session and the sequence number is used as a timestamp to order updates locally. The version vector encodes the causal dependencies of an update. It is a snapshot that identify the object versions present in the state cache. This version vector is in fact the last Global Stable Snapshot (section 2.3.3) EdgeAnt saw. EdgeAnt receives a new GSS in the following cases: when it syncs with the DC following a cache miss; after an update has been successfully propagated to a DC, the DC sends an acknowledgment to the client that contains the GSS assigned to this update; when a DC notifies the client of an external update.

The log cache sends these two elements with the update during the propagation to a DC. When a DC receives an update, it checks first if it did not already apply the update thanks to the client-assigned timestamp, preserving at-most-once delivery. Then, it checks that it has all the update's internal and external dependencies. Finally, it assigns the GSS to the update and stores it locally. The update will later be propagated to the other DC thanks to Cure replication protocol. As said earlier, the DC terminate the process by sending an acknowledgment to EdgeAnt with the assigned snapshot.

K-stability: A client can switch to a new DC at any time, in particular in response to a network failure or a crash. Since Antidote provides eventual consistency, there is no guarantee that an update delivered to the failed DC has been delivered to the other DCs. To maintain causal consistency, the client must observe a monotonically increasing progression of replica states. A client state can not "return in the past" if the new DC missed some updates. Therefore, availability will be reduced until the failed DC recover and propagate its updates. SwiftCloud's gives two answers to this problem. First, it makes the client cache co-responsible for the recovery of missing causal dependencies at the new DC. This solution is not sufficient, as the cache does not always contain all the missing dependencies needed to make the DC available for itself. The other solution brings by Swiftcloud is that the clients observe only its own updates and the K-stable updates from the other clients. An update is K-stable if it has been applied in at least K DCs, where K is configurable. The higher K is, the more we decrease the chance that the system be unavailable, however the more stale the data will be.

4 Contribution

We presented the current state of the system as studied during this internship. On the DC-side we have Antidote, a geo-replicated database that provides strong consistency and convergence guarantees with a high throughput. On the client side we have EdgeAnt, an extension of Antidote to the Edge that provides consistent partial replication on a client device, with built-in failure recovery. Clients can execute fast transactions locally and even offline. But client side execution is not always beneficial. For instance, computation that access a lot of data, such as search or recommendations is better done in the DC.

We had two main objectives during this internship. First, we had to implement a component placed between EdgeAnt and an Antidote data centre, that would allow an EdgeAnt client to offload a piece of code to be executed on the DC-side. The challenge of this first step is to ensure that the result of this remote execution is the same as that of a local execution. The value returned by the remote call and the state of the EdgeAnt cache must be the same that if the code had been executed on the client device. The second step was to choose and implement a scheduling strategy, that could dynamically decide where to execute a piece of code.

We failed to reach the second step and did not finish the implementation of the first step. What will be presented in the following subsection is the specification of the first step. We present what needs to be added to both Antidote and EdgeAnt interface, and the design of our solution.

4.1 Code offloading

This section described the specification of the code offloading module. We will refer to this module as CO for simplicity. The module can only upload Erlang code. This code can contain any Erlang built-in method and library. It can also call method from external libraries, if library has been uploaded too. The obvious security problems are not addressed in this internship. CO provides an interface to execute read-only transactions as well. This interface is duplicated on the client device and on the server. If this interface is used from the client device, it just executes EdgeAnt read transactions. If this interface is used from an offloaded code on a server, it will execute the transaction protocol that we will know describe.

Transaction protocol: CO offers the following methods to start a job and build read-only transactions: *start_job*, *start_transaction*, *read_objects* and *commit_transaction*.

When a client device starts a job remotely, it gives the snapshot on which the job executes. This snapshot is the last GSS seen by EdgeAnt. The GSS will permit CO to read data consistent with the cache of EdgeAnt. EdgeAnt also provides its local clock, so CO can check if it misses updates from this client. Finally, it gives its current interest set. This is necessary if the job read an object that is not in this set. In this case, CO will have to update the interest set on the DC and on the client at the end of the job.

When *read_objects* is called, CO will just ask the objects to Antidote as a regular client. If there is internal dependencies missing, CO makes a remote call to fetch them from the client's log cache. It then applies those updates on the read objects. CO do not transfer these updates to the DC, since it only provides read-only transactions, it lets EdgeAnt propagate those updates itself later.

commit_transaction closes the transaction but does nothing special since it is a read-only transaction.

Modification of EdgeAnt: EdgeAnt can invoke CO while some of its local updates have not been propagated to the DC. The state of EdgeAnt is therefore in advance compare to the DC. The reads made on the DC-side must see those updates, otherwise we would violate the invariant that clients must observe a monotonically increasing progression of replicas state. A simple solution is to have EdgeAnt synced with the DC before launching a job execution. This solution could increase the latency more than necessary by sending updates not necessary for the execution. We decide that CO will have to ask for missing update to EdgeAnt during the execution. Therefore, we need to add the following function to EdgeAnt interface: $get\_updates([Keys], Snapshot) : [Operation]$

Modification of Antidote:

One of the invariants our module needs to conserve is that an EdgeAnt client only reads its own updates and the K-stable updates from other clients. K-stability in EdgeAnt is tracked by a daemon in the client side. The tracking is made on the client side because one of the goal of EdgeAnt in the long term is to be able to have user-to-user communication. An application on a user device will look for data at the device of a client near by instead of contacting the DC. First, we thought that since our module is executed on the server side, we needed to add the capability in Antidote to read from a K-stable snapshot. It was a mistake. An EdgeAnt client provides the last GSS it saw to CO when it launches an execution. The architecture of EdgeAnt ensures that this snapshot includes only its own updates and K-stable updates from other clients. I progressed too much in the solution of this problem before realising it was not one in our case. We present it here as a contribution, because it presents a way to modify the Cure protocol to provide support for K-stability in an asynchronous way. This could be useful if we want to build a client other that EdgeAnt, that did not want to handle K-stability in the client-side.

To that end, we modify the Cure protocol explained in 2.3.3. We keep the mechanism of the Global Stable Snapshot and add a new Global K-stable Snapshot (GKSS).

We present the modification made to the Cure protocol to track K-stable updates. In the following pseudocode (Algo 1), we have a lighter version of the Cure protocol presented in [7]. We trim the code to the part necessary for replication between DC on the one hand and the computation of a Global Stable Snapshot by a partition on the other hand.

First, we explain the part of this pseudocode that is in Cure. The third row of Table 2 is added for our contribution and is not considered for the moment. We recall that in Cure, the database is partitioned and geo-replicated, we note p_d^m the partition m in DC d. The propagation of updates between replicas is made at the partition level.

In the function **propagate_transaction**, we can see how sibling partitions periodically communicate to send their local progress, i.e. local updates associated with a commit timestamp ct_T or just a heartbeat if there have been no updates. We note pvc_d^m the version vector maintains by the partition m at DC d. The entry of index i reflects the progress made by the partition p_i^m received by p_d^m, except for the entry m which represents the progression of p_d^m. This version vector is updated when a partition receives a heartbeat or a remote update. The entry m is incremented by the partition when it propagates update, but it is not shown here to simplify. When a partition sends a heartbeat, it just sends this vector as seen in line 11. In the functions **heartbeat** and **replicate_transaction**, we can see how pvc_d^m is updated, line 19 and 23. Now, the Cure protocol needs to decide which remote updates can be made visible. To that end, partitions within a DC periodically send their pvc. A partition m maintained the matrix PMC_d^m of all the received pvc and compute the GSS_d^m as the aggregate minimum of all pvc. we can see the periodic propagation of pvc in **bcast_pvc** and the computation of GSS_d^m in **update_GSS** line 41-42.

Now, we explain the pseudocode of our contribution to add K-stability in the protocol. We keep the GSS as it is because, we let the possibility to a user of Antidote that is not EdgeAnt to read no K-stable version. We recall that an update is K-stable if K DCs received it, K being a configurable number. Since in Cure the propagation of updates is made at the partition level, this is the role of the partitions to detect when an update is K-stable. Then, partitions compute a GSS of K-stable updates, called $GKSS$, in the same way we saw earlier. Intuitively, $GKSS$ is equal to GSS if $K = 1$. First, we explain the algorithm made by a partition to compute a local K-stable snapshot, implemented by the function **compute_pkvc**. When a partition p_d^m received a snapshot (a version vector) from a sibling partition, it saved it in a matrix $PMRemote_d^m$. This matrix has M rows and D columns and is initialized to zero line 3. To simplify the code, we define a function *kmax* that takes a vector and returns the k^{th} biggest element, k being the configuration chosen for the K-stability. For example, for $K = 2$ and a vector [11, 7, 5], *kmax* return 7, the 2^{th} biggest element.

Here an example of computation of K-stability to clarify: We have a system of 3 interconnected data centres, each having M partitions (not important here) and K is fixed at 2. We place ourselves in the DC 1 on the partition 2 noted p_1^2.

$$p_1^2\ has\ a\ pvc = [11, 4, 2]; \tag{1}$$

$$p_1^2\ received\ [7, 7, 3]\ and\ [4, 5, 3]\ from\ siblings\ p_2^2\ and\ p_3^2 \tag{2}$$

$$PMRemote_1^2 \ = \begin{bmatrix} 11 & 4 & 2 \\ 7 & 7 & 3 \\ 4 & 5 & 3 \end{bmatrix} \tag{3}$$

$$kmax\ with\ K = 2\ applied\ to\ each\ columns\ returns\ [7, 5, 3] \tag{4}$$

$$pkvc_1^2 = min([11, 4, 2], [7, 5, 3]) = [7, 4, 2] \tag{5}$$

- (1): [11, 4, 2] is the consistent view available at p_1^2, it means that it receives updates until snapshot 4 for p_2^2 and until 2 for p_3^2 and its current advancement is 11.
- (2): p_1^2 received heartbeats from siblings partitions.
- (3): p_1^2 updates $PMRemote_1^2$ accordingly. The first column is the progress of DC_1 available in the 3 DCs, the second column the progress of DC_2, etc...
- (4): *kmax* is applied on each column of the matrix and returns [7, 5, 3], this vector is a snapshot containing updates which are 2-stable between partition p^2 replicas.
- (5): The previous vector is not sufficient, we can see that the second entry 5 is not available at p_1^2 which is still at 4. So we compute the minimum between pvc_1^2 and the k-stable vector. The vector $pkvc_1^2$ obtained reflects the k-stable updates available at p_1^2.

This is how partitions compute k-stable vectors. We can see that there is a gap between pvc_1^2 ([11, 4, 2]) and $pkvc_1^2$ ([7, 4, 2]). Reading from K-stable updates increases staleness as said earlier. Afterwards, partitions can compute the GKSS the same way they do the GSS, as seen in line 40 and 43.

M	Number of partitions at a data centre
D	Number of data centres in the system
p_d^m	Partition m at DC d
pvc_d^m	Version vector at partition p_d^m -> updates received from siblings
PMC_d^m	Matrix of received pvc_d^i to compute GSS at p_d^m
GSS_d^m	Global Stable Snapshot of p_d^m, a version vector
$PMRemote_d^m$	Matrix of remote pvc_d^i received to compute $pkvc_d^m$
$pkvc_d^m$	Version vector at partition p_d^m -> k-stable updates received from siblings
$PMKC_d^m$	Matrix of received $pkvc_d^i$ from partitions of the DC to compute GKSS at p_d^m
$GKSS_d^m$	Global K-Stable Snapshot of p_d^m
T	Transaction
ct_T	Version vector assigned as T's commit snapshot
$committedTx_d^m$	Set of committed transactions at p_d^m
$ws_T[m]$	Set of updates made in transaction T by partition m

Table 2: Notation used in the protocol description

Algorithm 1 Cure protocol with K-stability executed at partition p_d^m

Init:
$pkvc_d^m[i] \leftarrow 0, i = 1...D$
$PMRemote_d^m[i] \leftarrow pkvc_d^m, i = 1...D$
$PMKC_d^m[i] \leftarrow pkvc_d^m, i = 1...M$
$GKSS_d^m[i] \leftarrow 0, i = 1...D$

function PROPAGATE_TRANSACTION() ▷ Run periodically
    if $committedTx_d^m = \emptyset$ **then**
        for $k = 1...D, k \neq d$ **do**
            send HEARTBEAT(pvc_d^m, d) to p_k^m
        return
    end if
    for all $\langle T, ws_T[m], ct_T \rangle \in committedTx_d^m$ **do**
        for $k = 1...D, k \neq d$ **do**
            send REPLICATE_TRANSACTION($ws_T[m], ct_T, d$) to p_k^m
            $committedTx_d^m \leftarrow committedTx_d^m \setminus \{T\}$

function HEARTBEAT(pvc, k)
    $pvc_d^m[k] \leftarrow pvc[k]$
    COMPUTE_PKVC(pvc, k)

function REPLICATE_TRANSACTION($ws_T[m], ct_T, k$)
    $pvc_d^m[k] \leftarrow ct_T[k]$
    COMPUTE_PKVC(ct_T, k)

function COMPUTE_PKVC($snapshot, k$)
    $Temp[i] \leftarrow 0, i = 1...D$ // Temporary vector
    $PMRemote_d^m[d] \leftarrow pvc_d^m$
    $PMRemote_d^m[k] \leftarrow snapshot$
    for $k = 1...D, k \neq d$ **do**
        $Temp_d^m[k] \leftarrow$ kmax *applied to column* k *of* $PMRemote_d^m$
    $pkvc_d^m \leftarrow \min_{i=1..D}(pvc_d^m[i], Temp[i])$

function BROADCAST_PVC() ▷ Run periodically
    for all $i = 1...M$ **do**
        send UPDATE_GSS($m, pvc_d^m, pkvc_d^m$) to p_d^i

function UPDATE_GSS($i, pvc, pkvc$)
    $PMC_d^m[i] \leftarrow pvc$
    $PMKC_d^m[i] \leftarrow pkvc$
    for $k = 1...D, k \neq d$ **do**
        $GSS_d^m[k] \leftarrow \min_{i=1..M} PMC_d^m[i][k]$
        $GKSS_d^m[k] \leftarrow \min_{i=1..M} PMKC_d^m[i][k]$

5 Future Work

As said in the previous section, we only started to think about the solution and its specification, when we reached the end of this internship. There is a lot of refining to do in the transaction protocol and off course it needs to be implemented and tested.

For the evaluation, we wanted to use FMKe, an application benchmark created to evaluate geo-replicated key-value stores providing weak consistency [10]. It is based on a real system: the Danish National Joint Medicine Card (FMK for Faelles Medicinkort). Using the data and access pattern of a realistic application provides relevant performance evaluation. Implementation of the benchmark exists for Antidote, so it seems like a good choice to evaluate the performance of our contribution and compared it to the current system. FMKe can be used to test a database in term of throughput or latency. To evaluate our work properly we also need to define consistency tests, especially in the presence of network partitions, but we haven't thought about how to create those tests.

The second step, after developing a fully functional code offloading module, is to integrate a scheduler in EdgeAnt. The goal is to dynamically determine if a piece of code should execute on the client device or on a data centre. We start looking in the domain of cyber foraging ([11]). Searchers in this field try to find efficient solution to offload code from a mobile device to nearby servers. The main challenge is to properly partition the application into pieces that can seamlessly be offloaded to a remote server. Pieces of an application well-suited for remote execution are parts that do not depend on external input, like input from an user or information from the material. Secondly, some side-effect must be avoided like writing on disk or modify the user interface. Finally, sending the request and its arguments and receiving its result should have a significantly lower cost than the perceived latency if the request had been executed on the client device. MAUI [12] for example, lets the developer decides which methods of an application are safe for remote execution with a special annotation. It handles the problem of executing the code on different type of architecture by using the Microsoft .NET Common Language Runtime, which means it only support applications coded in language support by this runtime like C#. Similarly, CloneCloud[13] runs on a modify JVM, and can support application coded in Java. In CloneCloud a static analysis of the application determines which method can be offloaded. Finally, our code offloading module runs on the Erlang virtual marchine and takes advantage of a language capability to unload binary code to a remote Erlang VM. We would probably choose the same solution of MAUI and let the developer defines which method can be offloaded.

Once the partitioning is done, the second challenge is to determine dynamically when an update must be executed on the client device or on a remote server. MAUI and CloneCloud dynamically takes this decision by profiling the application during the execution. They evaluate the "hot part" in terms of energy consumption or latency and check the current state of the device such as the battery level or the quality of the network connection among other things. We have not given much thought to this part of the problem extensively and it would be interesting to work on a solution for our use case.

6 Conclusion

At the beginning of our internship, we were assigned a different subject. Our first subject was to create a novel JSON op-based CRDT. Adding the capability to store JSON documents in the form of a CRDT would make of Antidote a powerful document store. The second part of this subject was to create a query language to manipulate those documents in an expressive way. We can think of point queries on text attribute or interval queries on numerical attribute for example. To make those queries efficient, support for secondary indexes must be added in Antidote. Working on this subject for two months, we studied the theory behind Antidote: The trade-off between consistency and availability explain in the CAP theorem [14], and the related work on consistency model, placing at different level of this trade-off. Off course, we studied CRDTs and explored ways to represent a document with an op-based CRDT ([15, 16]). And finally, we studied transaction models to understand the Cure protocol used by Antidote.

This subject has changed for the one we presented in this report. The reason was that other people had already work on it and it was more a technical challenge than a research one, so we lost interest for it. In this new subject, we wanted to add the possibility in Antidote to store code in a data centre. A developer could use this feature to store parts of an application that invokes heavy transactions. Those transactions would be executed on the DC side, which would avoid round-trip with the client and increase performance as explained in the introduction. Finally, we had the idea to extend this functionality to enable a client to decide dynamically if a piece of code must be executed on the client device or on a data centre. We needed to add the possibility to transfer code between a client device and an Antidote data centre. We wanted the result of this execution to be the same independently of where it originated. As said earlier, in our view of the system, a client is a device hosting EdgeAnt that communicates with one or more Antidote centre. To understand EdgeAnt, we needed to understand the issue of maintaining consistency guarantees between a data centre and a partial replica of the database pushed to the Edge.

In conclusion, during this internship, I study a wide range of academic work in the field of distributed databases. Consistency model, transaction protocol, partial replication to the Edge and code offloading to the Cloud; it was very challenging to place myself in those different research studies. I most certainly underestimated the difficulty to assimilate all those notions and did not correctly planned my work. By focusing on smaller objectives and communicating more with my advisors instead of working in isolation, I would probably have a better contribution to the Antidote project. It was nevertheless a pleasant experience in the world of research.

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