Abstract

Causal consistency for key-value stores has two main requirements (1) do not make a version visible if some of its dependencies are invisible as it may violate causal consistency in the future and (2) make a version visible as soon as possible so that clients have the most recent information (to the extent feasible). These two requirements conflict with each other. Existing key-value stores that provide causal consistency (or detection of causal violation) utilize a static approach in the trade-off between these requirements. Depending upon the choice, it assists some applications and penalizes some applications. We propose an alternative where the system provides a set of tracking groups and checking groups. This allows the application to choose the settings that are most suitable for that application. Furthermore, these groups can be dynamically changed based on application requirements.

1 Introduction

Causal consistency for distributed key-value stores has received much attention from academia in recent years. Existing protocols utilize a static approach in the trade-off between different conflicting requirements (e.g. consistency, visibility, and throughput). They also treat all clients the same, and assume that their usage patterns are always unchanged. For example, they assume clients only access their local data center, and any client may access any part of the data. However, different applications may have different usage patterns. To illustrate, consider a simple system that consists of two partitions A and B with geographically distributed copies A1, A2, B1 and B2. Suppose, we are using a causal consistency protocol like [7,8,11,12,14] that does not make a version visible, unless it made sure all partitions inside a replica are updated enough. We consider two possible ways to organize the replicas: (1) two full replicas each with two partitions, referred to as 2 × 2 or four partial replicas each with one partition referred to as 4 × 1. These two organizations are shown in Figure 1. Now, consider two applications. The first application, App1 consists of two clients C1 and C2 that access A1 and A2 respectively for a collaborative work. In App1, each client updates the data after it reads the new version written by another client. Since each client waits for the other client’s update, any increase in update visibility will reduce the throughput of App1. In the scenario in Figure 1(a) since A1 and B1 are considered in the same replica, A1 does not make versions visible, unless it made sure B1 is updated enough. Thus, if the communication between A1 and B1 is slow, it takes more time for A1 to make a version visible. Since the data on B1 and B2 is irrelevant for App1, this delay by A1 is unnecessary which leads to increased visibility latency which, in turn, leads to a reduced throughput of App1. Furthermore, if there were a large number of such partitions, this delay would be even more pronounced.

By contrast, there is no such penalty in scenario in Figure 1(b) as in Figure 1(b) partitions A1 and B1 are considered in different replicas. Thus, they do not check each other.

Figure 1: Two ways to organize replicas

On the other hand, consider App2 that consists of one client, say C3, and it accesses data from A1 and B1. In scenario in Figure 1(a) C3 is guaranteed to always read the consistent data. However, in scenario in Figure 1(b) since A1 and B1 do not check the freshness of each other, C3 may suffer from finding inconsistent versions (or delays or repeated requests to find a consistent version)
while accessing \( A_1 \) and \( B_1 \).

From the above discussion, it follows that no matter how we configure the given key-value store, a system with a static configuration that treats all clients the same will penalize some clients. The goal of this work is to develop a broad framework that instead of relying on a fixed set of assumptions, allows the system to be dynamically reconfigured after learning the actual client activities and requirements.

In Section 2 we propose an approach that lets us effectively trade off between different objectives and serve different groups of clients differently. Next, in Section 3 we provide a framework that uses our proposed approach. In Section 4 we discuss ideas for creating adaptive causal systems based on our protocol. Finally, in Section 5 we conclude the paper.

## 2 Adaptive Causal Consistency

The broad approach for providing causal consistency is to track the causal dependencies of a version, and check them before making the version visible in another replica. Tracking and checking are usually done using timestamping versions as follows:

- **Dependency Tracking**: Upon creating a new version for a key, we assign a timestamp to the version that somehow captures causal dependencies of the version.

- **Dependency Checking**: Upon receiving a version, the receiving replica does not make the version visible to the clients until it makes sure that all of the dependencies of the version are also visible to the clients.

The goal of timestamping is to provide a way to capture causal relation between two versions. To satisfy \( v_1 \text{dep} v_2 \iff v_1.t > v_2.t \) (where \( v_1 \text{dep} v_2 \) means the event of writing \( v_2 \) has happened before \( v_1 \) the event of writing \( v_1 \), and \( v.t \) is the timestamps assigned to \( v \)), we need timestamps of size \( O(N) \) where \( N \) is number of nodes that clients can write on. To solve the issue of large timestamps, causal consistency protocols consider servers in groups and track causality with vectors that have one entry per group. We refer to such groups as tracking groups. Tracking dependencies in groups, provides timestamps that satisfies a weaker condition \( v_1 \text{dep} v_2 \Rightarrow v_1.t > v_2.t \). This condition lets us guarantee causal visibility of the versions. However, since it does not provide accurate causality information, we may need to unnecessarily delay the visibility of a version by waiting for versions that are not its real dependencies. Thus, by grouping servers in tracking group, we trade off the visibility of versions for a lower metadata size.

### Table 1: Tracking and Checking in Some of Causal Systems

| Protocol         | Tracking   | Checking   |
|------------------|------------|------------|
| COPS [11]        | Per key    | Per Replica|
| Eigeg [12]       | Per key    | Per Replica|
| Orbe [7]         | Per server | Per Replica|
| GentleRain [8]   | Per system | Per Replica|
| Octo [13]        | Per Master Server | No checking |
| Okapi [6]        | Per Replica | Per system |
| CausalSpartan [14]| Per Replica | Per Replica |

We face a similar trade-off in the dependency checking. Dependency checking determines how conservative we are in making versions visible to the clients. Since checking the whole system is expensive, causal consistency protocols consider systems in groups, and each server only checks servers in its own group. We refer to such groups as checking groups. Most of current protocols [7,8,11,12,14,15] group servers by their replicas. Thus, a server only checks the dependencies inside the replica that it belongs to. Table 1 shows tracking and checking groups for some of the recent causal systems.

When we are designing a causally consistent key-value store, two natural questions arise based on the trade-offs explained above: 1) how much tracking accuracy is enough for a system? 2) how much should we be conservative in making versions visible? We believe the answer to these questions depends on the factors that should be learned at the run-time. A practical distributed data store performs in a constantly changing environment; the usage pattern of clients can change due to many reasons including time of the day in different time zones or changes in load balancing policies; data distribution can change, because we may need to add or remove some replicas; components may fail or slow down, and so on. These changes can easily invalidate assumptions made by existing causal consistency protocols such as [7,8,11,14] which leads to their reduced performance in practical settings [3]. To solve this issue, we believe that a key-value store must monitor the factors mentioned above and dynamically trade off between different conflicting objectives. We believe dynamically changing tracking and checking grouping based on what we learn from the system is an effective approach to perform such dynamic trade-offs. Using a flexible tracking and checking grouping we are also able to treat different applications in different ways.

To use the above approach, however, we need a protocol that can be easily configured for different groupings. As shown in Table 1 existing protocols assume fixed groupings that cannot be changed. To solve this issue, in the next section, we provide a protocol that can be configured to use any desired grouping. This flexible algorithm provides a basis for creating adaptive causal systems. This algorithm also lets us treat clients in differ-
ent ways, and unlike most of the existing protocols that require a certain data distribution schema, our algorithm allows us to replicate and partition our data any way we like including creating partial replicas.

3 Adaptive Causal Consistency Framework

In this section, we provide Adaptive Causal Consistency Framework (ACCF) which is a configurable framework that lets us deal with trade-offs explained in Section 3.2. Specifically, as the input, ACCF receives 1) function $T$ that assigns each server to exactly one tracking group, and 2) function $C$ that assigns each server to a non-empty set of checking groups.

3.1 Client-side

Algorithm 1 shows the client-side of the ACCF. A client $c$ maintains a set of pairs of tracking group ids and timestamps called dependency set, denoted as $DS_c$. For each tracking group $i$, there is at most one entry $(i, h)$ in $DS_c$ where $h$ specifies the maximum timestamp of versions read by client $c$ originally written in servers of tracking group $i$. Each data object has a key and a version chain containing different versions for the object. Each version is a tuple $(v, ds)$, where $v$ is the value of the version, and $ds$ is a list that has at most one entry per tracking group that capture dependency of the version on writes on different tracking groups.

```
Algorithm 1 Client operations at client $c$
Input: Load balancer $L$
1: GET (key $k$, checking group id $cg$)
2: $i = L(k)$
3: send (GETREQ $k, cg, DS_c$) to server $i$
4: receive (GETREPLY $d$)
5: $DS_c ← max(DS_c, d.ds)$
6: return $d.v$
7: PUT (key $k$, value $v$)
8: $i = L(k)$
9: send (PUTREQ $k, v, DS_c$) to server $i$
10: receive (PUTREPLY $tg, ut$)
11: $DS_c ← max(DS_c, \langle tg, ut \rangle)$
```

To read the value of an object, the client calls GET method with the desired key to read. The client also specifies the id of the checking group that the server must use. We will see how the server uses this id in Section 3.2. We find the preferred server to read the object using the given load balancer service $L$. After finding the preferred server to ask for the key, we send a GETREQ request to the server. In addition to the key and the checking group id, we include the client dependency set $DS_c$ in the request message. The server tries to find the most recent version that is consistent by the client’s past reads. In the Section 3.2, we explain how the server looks for a consistent version based on the $DS_c$.

The client sends a request to the server to ask for the key, we send a GET request message. The server tries to find the most recent id, we include the client dependency set $DS_c$ in the request message. In addition to the key and the checking group, periodically share their VVs with each other in case of not sending any message for a specific amount of time.

3.2 Server-side

In this section, we focus on the server-side of the protocol. We denote the physical clock at server $i$ by $PC_i$. To satisfy $v_1 \rightarrow dep v_2 \Rightarrow v_1.t > v_2.t$ condition, and assign timestamps close to the physical clocks, ACCF relies on Hybrid Logical Clocks (HLCs) [9]. $HLC_i$ is the value of HLC at server $i$. Each server keeps a version vector that has one entry for each tracking group denoted by $VV_i$. $VV_i[t]$ is the minimum of latest timestamps that server $i$ has received from servers in tracking group $t$. To keep each other updated, servers send heartbeat messages to each other.

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Once server $i$ receives a PUT request, the server updates $HLC_i$ by calling $updateHLC(dt)$ where $dt$ is the highest timestamp in $ds$.

The client writes the version and records client’s $DS_c$ as the dependency of the version. After receiving a response from the server for a GET (or PUT) operation, we update $DS_c$ such that any later version written by the client depends on the version read (or written) by this operation.

$V_i[T(i)]$ with the new $HLC_i$ value, and sends back its tracking group, $T(i)$, and the assigned timestamp, $d.ds[T(i)]$, to the client in a PUTREPLY message.
Upon creating a new version for an object in one server, we send the new version to other servers hosting the object via replicate messages. Upon receiving a \langle\text{REPLICATE } k,d\rangle message from server \textit{j}, the receiving server \textit{i} adds the new version to the version chain of the object with key \textit{k}. The server also updates the entry for server \textit{T}(\textit{j}) in its version vector (i.e., \textit{VV}_i[\textit{T}(\textit{j})]).

Algorithm 2 PUT and GET operations at server \textit{i}

\textbf{Input:} Tracking grouping function \textit{T}, Data placement function \textit{H}

1. \textbf{Upon} receive \langle\text{GETREQ } \textit{k}, \textit{cg}, \textit{ds}\rangle
2. \textbf{while} there is a member \langle\textit{t}, \textit{h}\rangle in \textit{ds}, \textit{h} > \textit{VV}_i[\textit{t}]
3. \hspace{1em} wait
4. \textbf{if} for all \langle\textit{t}, \textit{h}\rangle in \textit{ds}, \textit{h} > SVV^{\textit{cg}}[\textit{t}]
5. \hspace{1em} \textit{d} = latest version \textit{d} from version chain of key \textit{k} s.t. for any member \langle\textit{t}, \textit{h}\rangle in \textit{ds}, \textit{h} ≤ SVV^{\textit{cg}}[\textit{t}]
6. \textbf{else}
7. \hspace{1em} \textit{d} = latest version \textit{d} from version chain of key \textit{k}
8. \hspace{1em} send \langle\text{GETREPLY } \textit{d}\rangle to client
9. \textbf{Upon} receive \langle\text{PUTREQ } \textit{k}, \textit{v}, \textit{ds}\rangle
10. \hspace{1em} \textit{dt} ← maximum value in \textit{ds}
11. \hspace{1em} update\textit{HLC}(\textit{dt})
12. \hspace{1em} Create new item \textit{d}
13. \hspace{1em} \textit{d} = v, \max(\textit{ds}, \langle\textit{T}(\textit{i}), \textit{HLC}_i\rangle)
14. \hspace{1em} insert \textit{d} to version chain of \textit{k}
15. \hspace{1em} update \textit{VV}_i[\textit{T}(\textit{j})] with \textit{HLC}_j
16. \hspace{1em} send \langle\text{PUTREPLY } \textit{T}(\textit{i}), \textit{d}, \textit{ds}[\textit{T}(\textit{i})]\rangle to client
17. \hspace{1em} for each server \textit{j} ≠ \textit{i}, such that \textit{j} ∈ \textit{H}(\textit{k})
18. \hspace{2em} send \langle\text{REPLICATE } \textit{k}, \textit{d}\rangle to server \textit{j}
19. \textbf{Upon} receive \langle\text{REPLICATE } \textit{k}, \textit{d}\rangle from server \textit{j}
20. \hspace{1em} insert \textit{d} to version chain of key \textit{k}
21. \hspace{1em} update \textit{VV}_i[\textit{T}(\textit{j})] with \textit{d}, \textit{ds}[\textit{T}(\textit{j})]
22. \textbf{update\textit{HLC}}\textit{forPut}(\textit{dt})
23. \hspace{1em} \textit{l}’ ← \textit{HLC}_i, \textit{l}
24. \hspace{1em} \textit{HLC}_i, \textit{l} ← \max(\textit{l}’, \textit{PC}_i, \textit{dt})
25. \hspace{1em} if (\textit{HLC}_i, \textit{l} = \textit{l}’ = \textit{dt})
26. \hspace{2em} \textit{HLC}_i, \textit{c} ← \max(\textit{HLC}_i, \textit{c}, \textit{dt}) + 1
27. \hspace{2em} else if (\textit{HLC}_i, \textit{l} = \textit{l}’) \textit{HLC}_i, \textit{c} ← \textit{HLC}_i, \textit{c} + 1
28. \hspace{2em} else if (\textit{HLC}_i, \textit{l} = \textit{l}) \textit{HLC}_i, \textit{c} ← \textit{dt}, \textit{c} + 1
29. \hspace{2em} else \textit{HLC}_i, \textit{c} ← 0

3.3 Evaluation

We have implemented ACCF using DKVF [16]. You can find our implementation of ACCF in DKVF repository [15]. In this section, we provide the results of 2 × 2 and 4 × 1 groupings for applications \textit{App1} and \textit{App2} explained in Section 1. We run the system explained in Section 1 consisting of \textit{A1}, \textit{A2}, \textit{B1}, and \textit{B2} on different data centers of Amazon AWS [11]. Note that since we focus on partial replication, there is no assumption about \textit{A1} and \textit{B1} (respectively \textit{A2} and \textit{B2}) to be collocated.

Observations for \textit{App1}. \textit{App1} consists of two clients \textit{C1} and \textit{C2}. \textit{C1} writes the value 0 using \textit{A1}. \textit{C2} reads 0 (from \textit{A2}) and writes 1 (to \textit{A2}). Subsequently, \textit{C1} waits to read 1 and writes 2 and so on. The best scenario for this case is when you have only two partitions \textit{A1} and \textit{A2} in the system. Hence, we normalize the throughput with respect to this.

The results for \textit{App1} are shown in Figure 2 where 2 × 2 (respectively 4 × 1) corresponds to the organization in Figure 1(a) (respectively, Figure 1(b)). In Figure 2(a) locations of \textit{A1}, \textit{A2} and \textit{B1} are fixed, and we vary the location of \textit{B1} from California to Singapore (ordered based on increasing ping time from \textit{A1} located in California). In Figure 2(b) we keep the location of \textit{B1} fixed, but artificially add \textit{delay}_{B1} to any message sent by \textit{B1}. As we can see, by viewing the system as Figure 1(b), \textit{App1} performance is unaffected whereas viewing the system as Figure 1(a) performance drops by more than 50%.

Observations for \textit{App2}. In \textit{App2}, client \textit{C3} alternates reading from \textit{A1} and \textit{B1}. To provide fresh copies, another client writes the same objects on \textit{A2} and \textit{B2} respectively. Here, viewing the system as in Figure 1(b) drops the performance substantially as the message delay of \textit{B2} (\textit{delay}_{B2}) increases. This is due to blocking the GET operations while waiting for receiving consistent versions. By contrast, by viewing replicas as in Figure 1(a) performance remains unaffected. Throughputs are normalized with respect to the case where there is no update.

4 Discussion

In this section, we discuss how our approach differs from existing work on adaptive causal systems and identify future work that we are currently pursuing.
Dynamically adding or removing checking groups: Adding checking groups is a straightforward process. Each checking group is associated with a data structure (e.g., SVV in the algorithm provided in Section 3) that the servers need to maintain (in RAM). Hence, if we want to add a new checking group, the system can run the protocol to initialize these fields and make the new checking group available. Removing a checking group is somewhat challenging especially if some client is using it. In this case, we anticipate that the principle-of-locality would be of help. If a client has not utilized a checking group for a while, in most cases, all the data the client has read has been propagated to all copies in the system. In other words, if a client is using a checking group that has disappeared, we can have the client choose a different checking group. It is unlikely to lead to delays, as all replicas already have the data that the client has read. Two practical questions in removing checking groups are (1) the time after which we can remove a checking group and (2) how servers can determine that no client has accessed that checking group in that time. A more difficult question in this work is when to add a new checking group and how many checking groups to maintain. Clearly, we cannot create a checking group for each possible client, as it would require exponentially many checking groups.

Utilizing multiple checking groups simultaneously: Yet another question is whether clients could have multiple checking groups or whether clients can change their checking group. The former would be desirable when the system does not offer a checking group that the client needs. However, the client could choose two (or few) checking groups whose union is a superset of the checking group requested by the client. In this case, the server providing the data would have to utilize all of these checking groups –on the fly– to determine which data should be provided to the client.

Learning required checking groups automatically: In this case, the system will learn from client requests to identify when new checking groups should be added and when existing checking groups should be removed. We expect that dynamically changing the checking groups in this manner would be beneficial due to principle-of-locality, where clients are likely to access data that similar to the data they accessed before. (Recall that we assume that keys are partitioned with semantic knowledge rather than by approaches such as uniform hashing). We anticipate that learning techniques such as evolutionary or machine learning techniques would be useful to identify the checking groups that one should maintain.

Dynamically changing the tracking groups: Dynamically changing the tracking groups is more challenging but still potentially feasible in some limited circumstances. The reason for this is that while checking groups affect the data maintained by the servers at runtime (in RAM) tracking groups affect storage affected by keys (in long-term permanent storage). In other words, at runtime, we may run into a key that was stored with a different tracking groupings. In this case, it is necessary to convert the data stored with the old tracking grouping into the corresponding data in the new tracking grouping. We expect that principle-of-locality would be of help in this context as well; keys stored long ago are likely to have been updated in all replicas. Conversion of the data stored with keys is protocol specific but still feasible. For example, if we wanted to switch between tracking grouping used by CausalSpartan [14] (where a vector DSV is maintained with one entry per replica) to GentleRain [8] (where only a scalar entry GST is maintained) then we could convert the DSV entry into a GST entry that corresponds to the minimum of the DSV entries. However, the exact approach to do this for different tracking groupings requires semantic knowledge of those tracking groupings.

Comparison with related work: Our approach for providing adaptivity in causal consistency is different from other approaches considered in the literature. Ocult [13] utilizes structural compression to reduce the size of the timestamps. Other approaches include bloom filters [4]. While these features are intended as a configurable parameter, we believe that it is not possible to dynamically change it at run-time while preserving causal consistency (or detection of its violation). Furthermore, in all these cases, the reconfiguration provided is client-agnostic; it does not take client requests into consideration. By contrast, our framework provides the ability to allow different clients a view of the system in a manner that improves their performance. Finally, it is possible to take client requests into consideration to identify how adaptivity should be provided.

5 Conclusion

In this paper, we focused on developing a system that provides causal consistency in an adaptive manner. Specifically, we introduced the notion of tracking and checking groups as a way to generalize existing protocols as well as to develop new adaptive protocols. We provided a framework that, unlike existing causal consistency protocols, can be configured to work with different tracking and checking groupings. This flexibility enables us to trade off between conflicting objectives, and provide different views to different applications so that each application gets the best performance. We argue that the approach and the framework introduced in this paper provide a basis for adaptive causal consistency for replicated data stores.
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