Causal Consistency for Geo-Replicated Cloud Storage under Partial Replication

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Outline

Introduction

- Data Replication - a technique for fault tolerance in distributed systems
  Reduces **access latency** in the **cloud** and **geo-replicated** systems.
- Consistency of data - a core issue in the distributed shared memory
- Consistency Models
  Represent a trade-off (cost V.S. convenient semantics)
  - linearizability (the strongest)
  - sequential consistency
  - **causal consistency** [1]
  - pipelined RAM
  - slow memory
  - eventual consistency (the weakest)
- Industry interest
  For example, Google, Amazon, Microsoft, Facebook, LinkedIn

Geo-Replicated Cloud Storage Features

- CAP theorem (*Brewer*, 2000)≡ cannot provide all 3 features in the same system
    - Consistency of Replicas
    - Availability of Writes
    - Partition Tolerance
- low Latency
- high Scalability

Related Works

- **Causal consistency** in distributed shared memory systems (Ahamad et al.)
- **Causal consistency** has been studied (by Baldoni et al., Mahajan et al., Belaramani et al., Petersen et al.).
- In the past four years,
  - **ChainReaction** (S. Almeida et al.)
  - **Bolt-on causal consistency** (P. Bailis et al.)
  - **Orbe** and **GentleRain** (J. Du et al.)
  - **Wide-Area Replicated Storage** (K. Lady et al.)
  - **COPS, Eiger** (W. Lloyd et al.)
- The above works assume full replication.

Partial Replication

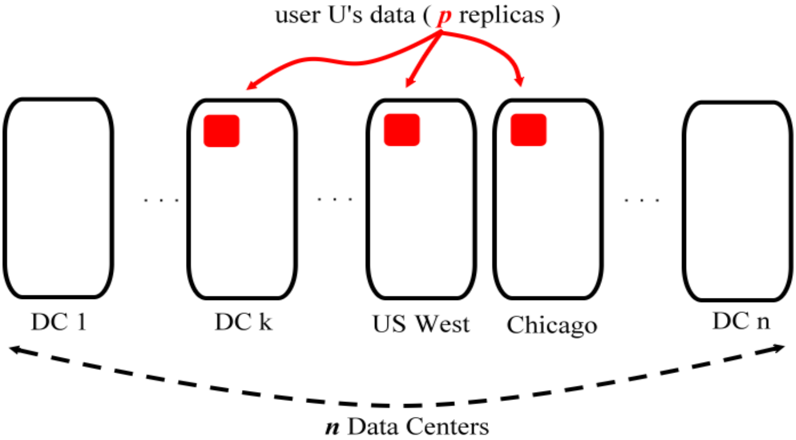


Figure : Case for Partial Replication.

Case for Partial Replication

- Partial replication is more natural for some applications. As shown in the previous case, ...
  - With p replicas places at some p of the total of n DCs, each write operation that would have triggered an update broadcast to the n DCs now becomes a multicast to just p of the n DCs.
- For write-intensive workloads, partial replication gives a direct savings in the number of messages.
- Allowing flexibility in the number of DCs required in causally consistent replication remains an interesting aspect of future work.
- The supposedly higher cost of tracking dependency metadata is relatively small for applications such as Facebook.

System Model

- A system with n application processes - ap_1, ap_2,...,ap_n - interacting through a shared memory $\mathcal{Q}$ composed of q variables x_1,x_2,...,x_q
- Each ap_i can perform either a *read* or a *write* operation on any of the q variables.
  - $r_i(x_j)v$: a **read** operation performed by ap_i on variable x_j which returns value v
  - $w_i(x_j)v$: a **write** operation performed by ap_i on variable x_j which writes value v
  - Each variable has an initial value $\perp$.
- local history h_i: a series of *read* and *write* operations generated by process ap_i
- global history H: the set of local histories h_i from all n application processes

Causally Consistent Memory [1]

- *Program Order*: under which a local operation o_1 precedes another operation o_2, denoted as $o_1 \prec_{po} o_2$
- *Read-from Order*: there are variable x and value v such that *read* operation $o_2 = r(x)v$ retrieves the value v written by the *write* operation $o_1 = w(x)v$ from a distinct process, denoted as $o_1 \prec_{ro} o_2$
  - for any operation o_2, there is at most one operation o_1 such that $o_1 \prec_{ro} o_2$
  - if $o_2 = r(x)v$ for some x and no operation o_1 such that $o_1 \prec_{ro} o_2$, then $v = \perp$
- *Causality Order*: for two operations o_1 and o_2 in O_H, $o_1 \prec_{co} o_2$ if and only if one of the following conditions holds:
  - $\exists ap_i$ s.t. $o_1 \prec_{po} o_2$ (program order)
  - $\exists ap_i$, ap_j s.t. $o_1 \prec_{ro} o_2$ (read-from order)
  - $\exists o_3 \in O_H$ s.t. $o_1 \prec_{co} o_3$ and $o_3 \prec_{co} o_2$ (transitive closure)

Underlying Distributed Communication System

- The **shared memory** abstraction and its **causal consistency** model is implemented on top of the **distributed message passing** system.
- With n sites (connected by FIFO channels), each site s_i hosts an application process ap_i and holds only a subset of variables $x_h \in \mathcal{Q}$.
- When an application process ap_i performs a write operation $w(x_1)v$, it invokes the **Multicast**(m) to deliver the message m containing $w(x_1)v$ to all sites replicating x_1.
- When an application process ap_i performs a read operation $r(x_2)v$, it invokes the **RemoteFetch**(m) to deliver the message m containing $r(x_2)v$ to a pre-designated site replicating x_2 to fetch its value.

Events Generated at Each Site

- *Send event.* **Multicast**(m) by ap_i generates event $send_i(m)$.
- *Fetch event.* **RemoteFetch**(m) by ap_i generates event $fetch_i(m)$.
- *Message receipt event.* The receipt of a message m at site s_i generates event $receipt_i(m)$.
- *Apply event.* Applying the value written by $w_j(x_h)v$ to x_h's local replica at ap_i, an event $apply_i(w_j(x_h)v)$ is generated.
- *Remote return event.* After the occurrence of $receipt_i(m)$ corresponding to the remote $r_j(x_h)u$ performed by ap_j, an event $remote\_return_i(r_j(x_h)u)$ is generated to transmit x_h's value u to site s_j.
- *Return event.* Event $return_i(x_h, v)$ corresponding to the return of x_h's value v either through a previous $fetch_i(f)$ event or read from the local replica.

Activation Predicate

- Baldoni et al. [2] defined a new relation, $\rightarrow_{co}$, on *send events*.
- Let $w(x)a$ and $w(y)b$ be two write operations in O_H. For their corresponding send events, $send_i(m_{w(x)a}) \rightarrow_{co} send_j(m_{w(y)b})$ iff one of the following conditions holds:
  1. $i = j$ and $send_i(m_{w(x)a})$ locally precedes $send_j(m_{w(y)b})$
  2. $i \neq j$ and $return_j(x, a)$ locally precedes $send_j(m_{w(y)b})$
  3. $\exists send_k(m_{w(z)c})$, s.t. $send_i(m_{w(x)a}) \rightarrow_{co} send_k(m_{w(z)c}) \rightarrow_{co} send_j(m_{w(y)b})$
- $\rightarrow_{co} \subset \rightarrow$ (Lamport's **happened before** relation)
- With the $\rightarrow_{co}$ relation, an optimal activation predicate is shown:

$$A_{OPT}(m_w, e) \equiv \nexists m_{w'} : (send_j(m'_w) \rightarrow_{co} send_k(m_w) \wedge apply_i(w') \notin E_i \mid_e) \quad (1)$$

- It is optimal because the moment this $A_{OPT}(m_w, e)$ becomes true is the earliest instant that the update m_w can be applied.

Algorithms

- Two algorithms implement causal consistency in a partially replicated distributed shared memory system.
  - **Full-Track**
  - **Opt-Track** (a message and space optimal algorithm)
- Adopt the optimal activation predicate A_{OPT}
- A special case of **Opt-Track** - for full replication.
  - **Opt-Track-CRP** (optimal) : a lower message size, time, space complexity than the Baldoni et al. algorithm [2]

Algorithm 1: Full-Track

- Algorithm 1 is for a **non-fully replicated** system.
- Each application process performing write operation will only write to a subset of all the sites.
- Each site s_i needs to track the number of write operations performed by every ap_j to every site s_k, denoted as $Write_i[j][k]$.
- the *Write* clock piggybacked with messages generated by the **Multicast**(m) should not be merged with the local *Write* clock at the message reception, but only at a later read operation reading the value that comes with the message.
    - optimal in terms of the activation predicate

Algorithm 1: Full-Track

- Data structures
  1. $Write_i$ - the *Wrtie* clock
     $Write_i[j, k]$: the number of updates sent by application process ap_j to site s_k that causally happened before under the $\rightarrow_{co}$ relation.
  2. $Apply_i$ - an array of integers
     $Apply_i[j]$: the total number of updates written by application process ap_j that have been applied at site s_i.
  3. $LastWriteOn_i\langle$variable id, $Write\rangle$ - a hash map of *Write* clocks
     $LastWriteOn_i\langle h\rangle$: the *Write* clock value associated with the last write operation on variable x_h locally replicated at site s_i.

Algorithm 1: Full-Track

WRITE(x_h, v):

for *all sites* s_j *that replicate* x_h **do**

  $Write_i[i,j]++$;

`Multicast`$[m(x_h, v, Write_i)]$ to all sites s_j $(j \neq i)$ that replicate x_h;

if x_h *is locally replicated* **then**

  $x_h := v$;

  $Apply_i[i]++$;

  $LastWriteOn_i\langle h \rangle := Write_i$;

READ(x_h):

if x_h *is not locally replicated* **then**

  `RemoteFetch`$[f(x_h)]$ from predesignated site s_j that replicates x_h to get x_h and $LastWriteOn_j\langle h \rangle$;

  $\forall k, l \in [1 \ldots n], Write_i[k,l] := \max(Write_i[k,l], LastWriteOn_j\langle h \rangle.Write[k,l])$;

else

  $\forall k, l \in [1 \ldots n], Write_i[k,l] := \max(Write_i[k,l], LastWriteOn_i\langle h \rangle.Write[k,l])$;

return x_h;

Algorithm 1: Full-Track

The activation predicate A_{OPT} is implemented.

On receiving $m(x_h, v, W)$ from site s_j:

wait until
$(\forall k \neq j, Apply_i[k] \geq W[k,i] \wedge Apply_i[j] = W[j,i] - 1)$;
$x_h := v$;
$Apply_i[j] + +$;
$LastWriteOn_i\langle h \rangle := W$;

On receiving $f(x_h)$ from site s_j:

return x_h and $LastWriteOn_i\langle h \rangle$ to s_j;

Algorithm 2: Opt-Track

- Each message corresponding to a write operation piggybacks an $O(n^2)$ matrix in **Algorithm 1**.
- **Algorithm 2** further reduces the **message size** and **storage cost**.
  - Exploits the transitive dependency of causal deliveries of messages as given by the KS algorithm [3][4]
- Each site keeps a record of the most recently received message from each other site (along with the list of destinations of the message).
  - optimal in terms of the activation predicate
  - optimal in terms of log space and message space overhead
  - achieve another optimality that no redundant destination information is recorded.

Two Situations for Destination Information to be Redundant

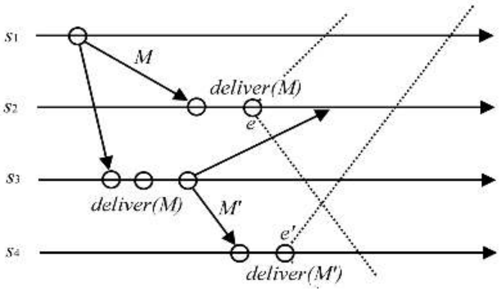


Figure : s_2 is a destination of M. The causal future of the relevant message delivery events are shown in dotted lines.

Two Situations for Destination Information to be Redundant

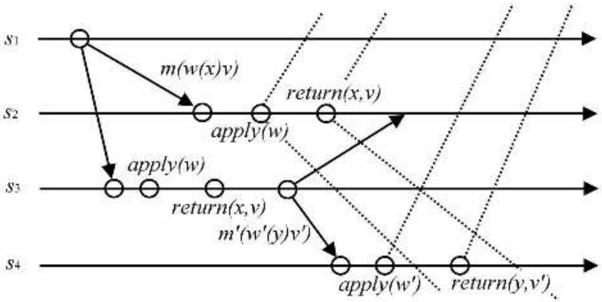


Figure : s_2 is a destination of m. The causal future of the relevant *apply* and *return* events are shown in dotted lines.

If the Destination List Becomes ∅, then ...

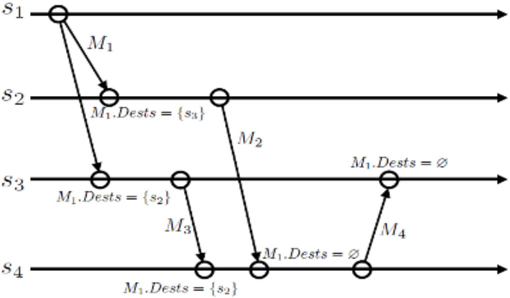


Figure : Illustration of why it is important to keep a record even if its destination list becomes empty.

Algorithm 2: Opt-Track

- Data Structures
  1. $clock_i$
     local counter at site s_i for write operations performed by application process ap_i.
  2. $Apply_i$ - an array of integers
     $Apply_i[j]$: the total number of updates written by application process ap_j that have been applied at site s_i.
  3. $LOG_i = \{\langle j, clock_j, Dests\rangle\}$ - the local log
     Each entry indicates a write operation in the causal past.
  4. $LastWriteOn_i\langle$variable id, $LOG\rangle$ - a hash map of $LOGs$
     $LastWriteOn_i\langle h\rangle$: the piggybacked LOG from the most recent update applied at site s_i for locally replicated variable x_h.

Algorithm 2: Opt-Track

WRITE(x_h, v):

$clock_i++$;
for *all sites* $s_j (j \neq i)$ *that replicate* x_h **do**
    $L_w := LOG_i$;
    for *all* $o \in L_w$ **do**
        if $s_j \notin o.Dests$ **then**
        $o.Dests := o.Dests \setminus x_h.replicas$;
        else $o.Dests := o.Dests \setminus x_h.replicas \cup \{s_j\}$;
    for *all* $o_{z,clock_z} \in L_w$ **do**
        if $o_{z,clock_z}.Dests = \emptyset \wedge (\exists o'_{z,clock'_z} \in L_w | clock_z <$
        $clock'_z)$ **then** remove $o_{z,clock_z}$ from L_w;
    send $m(x_h, v, i, clock_i, x_h.replicas, L_w)$ to site s_j;
for *all* $l \in LOG_i$ **do**
    $l.Dests := l.Dests \setminus x_h.replicas$;
PURGE;
$LOG_i := LOG_i \cup \{\langle i, clock_i, x_h.replicas \setminus \{s_i\}\rangle\}$;
if x_h *is locally replicated* **then**
    $x_h := v$;
    $Apply_i[i]++$;
    $LastWriteOn_i\langle h\rangle := LOG_i$;

Figure : Write process at site s_i

Algorithm 2: Opt-Track

READ(x_h):

if *x_h is not locally replicated* **then**

  `RemoteFetch`$[f(x_h)]$ from predesignated site s_j that replicates x_h to get x_h and $LastWriteOn_j\langle h\rangle$;

  `MERGE`$(LOG_i, LastWriteOn_j\langle h\rangle)$;

else `MERGE`$(LOG_i, LastWriteOn_i\langle h\rangle)$;

`PURGE`;

return x_h;

On receiving $m(x_h, v, j, clock_j, x_h.replicas, L_w)$ from site s_j:

for *all* $o_{z,clock_z} \in L_w$ **do**

  if $s_i \in o_{z,clock_z}.Dests$ **then** wait until $clock_z \leq Apply_i[z]$;

$x_h := v$;

$Apply_i[j] := clock_j$;

$L_w := L_w \cup \{\langle j, clock_j, x_h.replicas\rangle\}$;

for *all* $o_{z,clock_z} \in L_w$ **do**

  $o_{z,clock_z}.Dests := o_{z,clock_z}.Dests \setminus \{s_i\}$;

$LastWriteOn_i\langle h\rangle := L_w$;

On receiving $f(x_h)$ from site s_j:

return x_h and $LastWriteOn_i\langle h\rangle$ to s_j;

Figure : Read, receiving processes at site s_i

Procedures used in Opt-Track

PURGE:

for *all* $l_{z,t_z} \in LOG_i$ **do**

  if $l_{z,t_z}.Dests = \emptyset \wedge (\exists l'_{z,t'_z} \in LOG_i | t_z < t'_z)$ **then**

    remove l_{z,t_z} from LOG_i;

MERGE(LOG_i, L_w):

for *all* $o_{z,t} \in L_w$ *and* $l_{s,t'} \in LOG_i$ *such that* $s = z$ **do**

  if $t < t' \wedge l_{s,t} \notin LOG_i$ **then** mark $o_{z,t}$ for deletion;

  if $t' < t \wedge o_{z,t'} \notin L_w$ **then** mark $l_{s,t'}$ for deletion;

  delete marked entries;

  if $t = t'$ **then**

    $l_{s,t'}.Dests := l_{s,t'}.Dests \cap o_{z,t}.Dests$;

    delete $o_{z,t}$ from L_w;

$LOG_i := LOG_i \cup L_w$;

Figure : PURGE and MERGE functions at site s_i

Algorithm 3: Opt-Track-CRP

- Special case of Algorithm 2 Opt-Track for full replication.
- Same optimizations as for Algorithm Opt-Track.
- Since in the **full replication** case, every **write** operation will be sent to exactly the same set of sites, there is no need to keep a list of the destination information with each **write** operation.
- Each time a **write** operation is sent, all the **write** operations it piggybacks as its dependency will share the same set of destinations as the one being sent, thus their destination list will be pruned.
- When a **write** operation is received, all the **write** operations it piggybacks also have the receiver as part of their destination.
- We represent each individual **write** operation using only a 2-tuple $\langle i, clock_i \rangle$ at site s_i.
- the cost of a **write** operation from $O(n)$ down to $O(1)$.

Further Improved Scalability

- In Algorithm 2, keeping entries with empty destination list is important.
- In the fully replicated case, we can also decrease this cost.

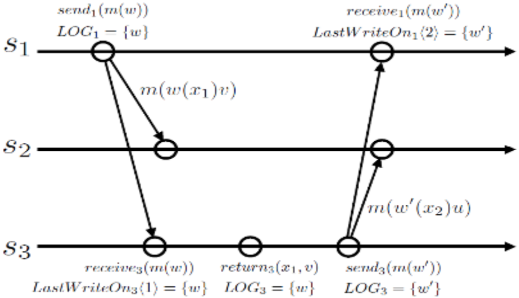


Figure : In fully replicated systems, the local log will be reset after each write operation.

Algorithm 3: Opt-Track-CRP

WRITE(x_h, v):
$clock_i++$;
send $m(x_h, v, i, clock_i, LOG_i)$ to all sites other than s_i;
$\boxed{LOG_i := \{\langle i, clock_i \rangle\};}$
$x_h := v$;
$Apply_i[i] := clock_i$;
$LastWriteOn_i\langle h \rangle := \boxed{\langle i, clock_i \rangle}$

READ(x_h):
MERGE($LOG_i, LastWriteOn_i\langle h \rangle$);
return x_h;

On receiving $m(x_h, v, j, clock_j, L_w)$ from site s_j:
for *all* $o_{z,clock_z} \in L_w$ **do**
  wait until $clock_z \leq Apply_i[z]$
$x_h := v$;
$Apply_i[j] := clock_j$;
$LastWriteOn_i\langle h \rangle := \boxed{\langle j, clock_j \rangle}$

MERGE($LOG_i, \langle j, clock_j \rangle$):
for *all* $l_{s,t} \in LOG_i$ *such that* $s = j$ **do**
  if $t < clock_j$ **then** delete $l_{s,t}$ from LOG_i;
$\boxed{LOG_i := LOG_i \cup \{\langle j, clock_j \rangle\};}$

Figure : There is no need to maintain the destination list for each write operation in the local log.

Parameters

- n: the number of sites in the system
- q: the number of variables in the distributed shared memory system
- p: the replication factor, i.e., the number of sites where each variable is replicated
- w: the number of write operations performed in the distributed shared memory system
- r: the number of read operations performed in the distributed shared memory system
- d: the number of write operations stored in local log (used only in Opt-Track-CRP algorithm)

Complexity

Metric	Full-Track	Opt-Track	Opt-Track-CRP	*OptP*
Message count	$pw + 2r\frac{(n-p)}{n}$	$pw + 2r\frac{(n-p)}{n}$	nw	nw
Message size	$O(n^2pw + nr(n-p))$	$O(n^2pw + nr(n-p))$ amortized $O(npw + r(n-p))$	$O(nwd)$	$O(n^2w)$
Time Complexity	write $O(n^2)$ read $O(n^2)$	write $O(n^2p)$ read $O(n^2)$	write $O(n)$ read $O(1)$	write $O(n)$ read $O(n)$
Space Complexity	$O(npq)$	$O(npq)$ amortized $O(pq)$	$O(max(n, q))$	$O(nq)$

Figure : Complexity measures of causal memory algorithms for fully-replicated memory. *OptP*: Optimal propagation-based protocol proposed by Baldoni et al. [2].

Comparisons

- Compared with $OptP$, our algorithms also adopt the optimal activation predicate A_{OPT} but incur a lower cost in the message size, space, and time (for read and write operations) complexities.
- Compared with other causal consistency algorithms, our algorithms have the additional ability to implement causal consistency in **partially replicated** distributed shared memory systems.
- Our algorithms provide scalability without using a form of log serialization and exchange to implement causal consistency.

The Benefit of Partial Replication V.S. Full Replication

- Reduces the number of messages sent with each write operation. The overall number of messages can be lower if the **replication factor** is low and readers tend to read variables from the **local replica** instead of **remote one** (e.g., Hadoop HDFS and MapReduce).
- Also reduces the total size of messages transmitted with the system (Consider the size of the data that is actually being replicated). Modern social multimedia networks are such examples.
- Decreases the cost brought by full replication in the write-intensive workload.

Message Count as a Function of w_{rate}

- Message count is the most important metric.
- Partial replication gives a lower message count than full replication if

$$pw + 2r\frac{(n-p)}{n} < nw \Rightarrow w > 2\frac{r}{n} \tag{2}$$

$$w_{rate} = \frac{w}{w+r} \Rightarrow w_{rate} > \frac{2}{2+n} \tag{3}$$

Partial Replication versus Full Replication

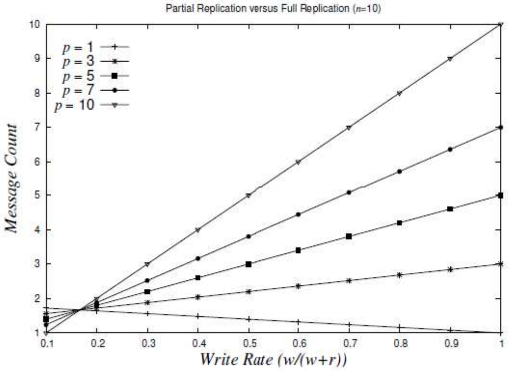


Figure : The graph illustrates message count for partial replication vs. full replication, by plotting message count as a function of w_{rate}.

Simulation Parameters of KS algorithm

- n : Number of processes
- **MIMT** - Mean intermessage time : the average period of time between two message sending events at any process
- **M/T** - Multicast frequency : the ratio of the number of send events at which data is multicast to more than one process (**M**) to the total number of message send events (**T**)
- **MTT** - Mean transmission time : the transmission time of a message usually refers to the *message size/bandwidth+propagation delay*.
- **B/T** : the fraction of send events that broadcast messages
- Baseline is n^2 matrix size of RST algorithm.

Average message space overhead as a function of n

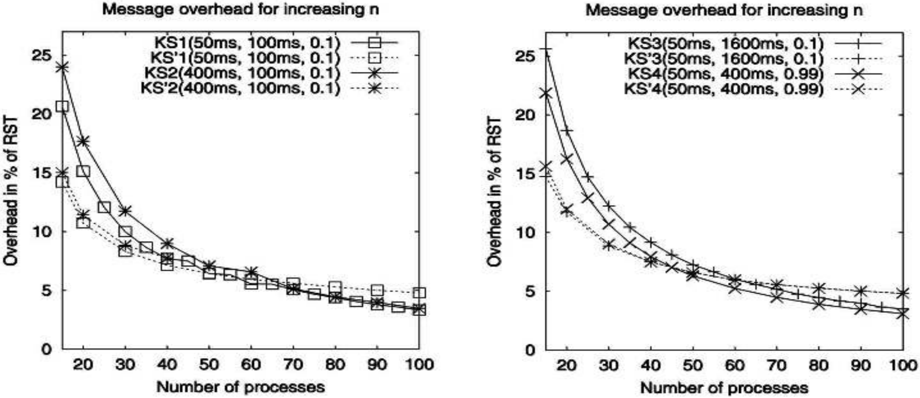
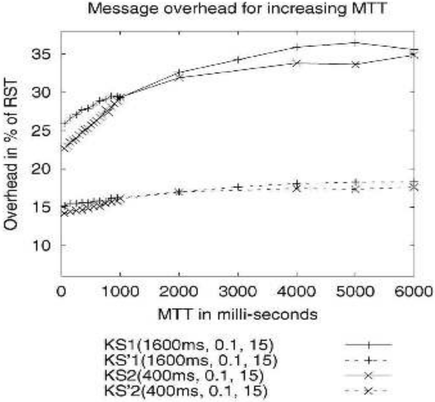


Figure : The simulations were performed for (MTT, MIMT, M/T).

Average Message Space Overhead as a Function of MTT



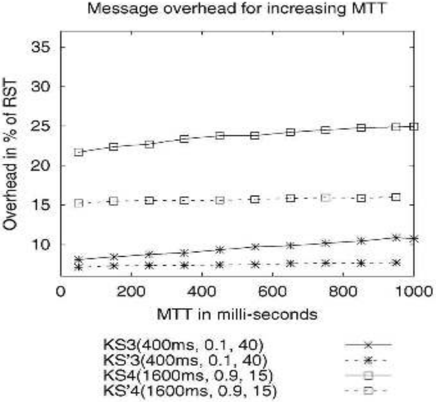
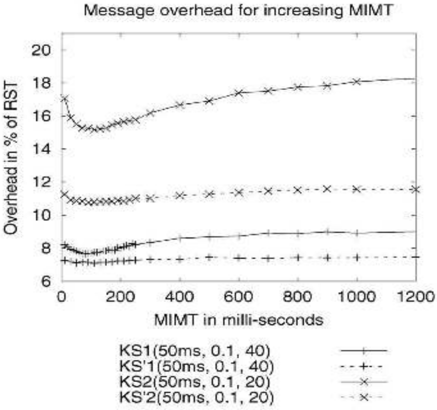


Figure : The simulations were performed for (MIMT, M/T, n).

Average Message Space Overhead as a Function of $MIMT$



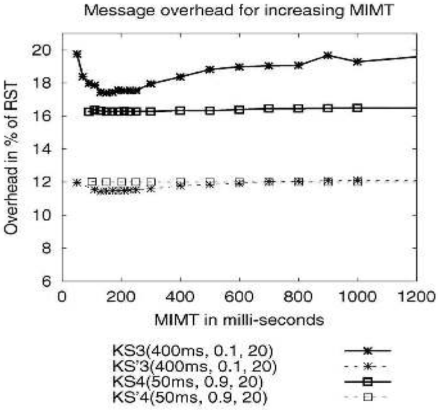


Figure : The simulations were performed for (MTT, M/T,n).

Average Message Space Overhead as a Function of M/T

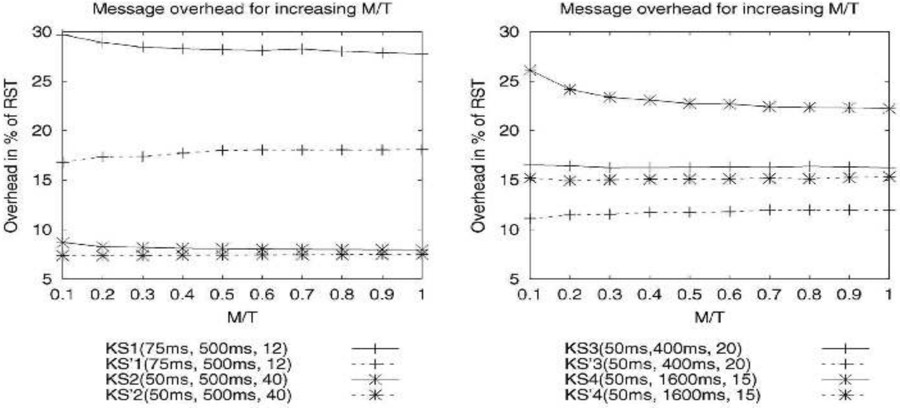


Figure : The simulations were performed for (MTT, MIMT, n).

Average Message Space Overhead as a Function of $|Dests|/n$

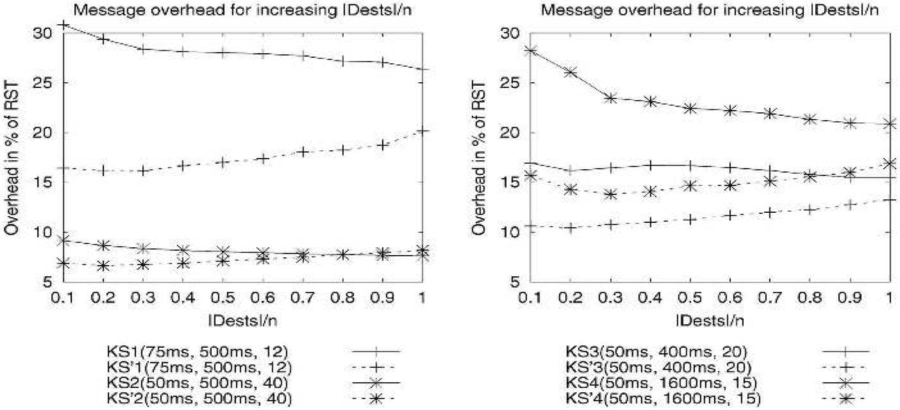


Figure : The simulations were performed for (MTT, MIMT, n).

Average Message Space Overhead as a Function of B/T

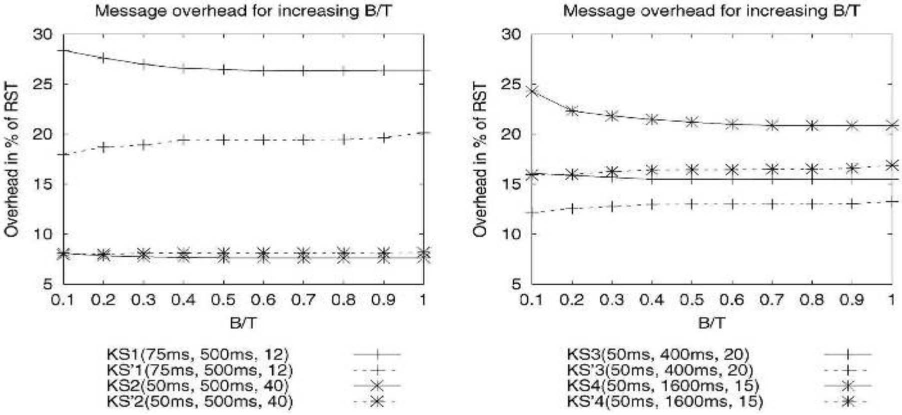


Figure : The simulations were performed for (MTT, MIMT, n).

Future Work

- For some applications where the data size is small (e.g, wall posts in Facebook), the size of the meta-data can be a problem.
  - quadratic in n in the worst case, even for Algorithm Opt-Track
- Future work aims to reduce the size of the meta-data for maintaining causal consistency in partially replicated systems.

Notion of Credits

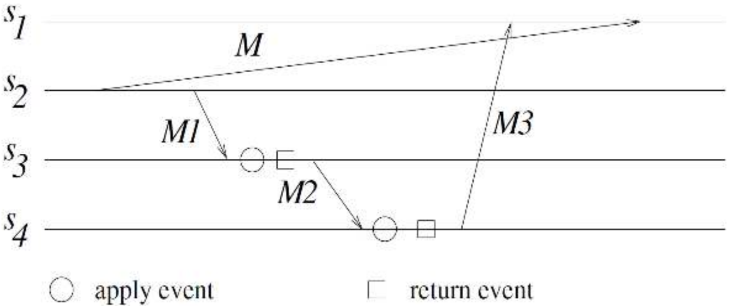


Figure : Reduce the meta-data at the cost of some possible violations of causal consistency. The amount of violations can be made arbitrarily small by controlling a tunable parameter (*credit*).

Instantiation of Credits

- Integrate the notion of credits into the Opt-Track algorithm, to give an algorithm that can fine-tune the amount of causal consistency by trading off the size of meta-data overhead.
- Give three instantiations of the notion of credits (*hop count*, *time-to-live*, and *metric distance*)

Conclusions

- A suite of algorithms implementing causal consistency in large-scale geo-replicated storage under **partial replication**.
- For the **partially replicated** scenario, adopted the optimal activation predicate in the sense that each update is applied at the earliest instant while removing false causality:
  - **Full-Track** Algorithm
- The second algorithm further minimizes the size of meta-information carried on messages and stored in local logs.
  - **Opt-Track** Algorithm: partially replicated scenario
  - Provides less overhead (transmission and storage) than the full replication case.
- A derived optimized algorithm of the second one reduces the **message overhead**, the **processing time**, and the **local storage cost** at each site in the fully replicated scenario.
  - **Opt-Track-CRP** Algorithm

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