Consistify: A Framework for Safe and Fair Execution of Concurrent SLA-driven Client Applications on Quorum-based Datastores

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Abstract. Distributed datastores often tradeoff correctness guarantees in favor of availability and partition tolerance, hence they can not simultaneously ensure correctness of application execution and at the same time satisfy latency requirements, especially with concurrent executions. We investigate the problem of preserving the correctness in quorum-based datastores under concurrent application executions, while satisfying the latency threshold in the SLA (Service Level Agreement). Consider a sequence of (or a single) operations on a distributed datastore invoked from a client application, with a application-level latency threshold specified in the SLA, and the correctness condition specified by the user as post conditions. The latency and the correctness of the given operations can be controlled by tuning the client-centric consistency settings of quorum-based distributed datastores. We present Consistify, a novel framework that can enable execution of client application on quorum-based datastores with the weakest possible consistency setting, while preserving the correctness, and at the same time satisfying the latency threshold in the SLA. Consistify enables safe and fair execution of concurrent client applications on quorum-based datastores under a given correctness condition and a latency threshold specified in the SLA. Consistify can determine provably valid client-centric consistency setting on quorum-based datastores, while simultaneously satisfying the latency threshold in the SLA and preserving the correctness condition.

1 Introduction

Quorum-based distributed datastores often tradeoff support for serializability and transactions in favor of availability and partition tolerance, hence they can not simultaneously ensure correctness of application execution and at the same time satisfy latency requirements, especially with concurrent executions. In this context, by correctness we primarily deal with the application level safety properties (liveness is handled internally by the datastore), like anomalies observed by the client due to conflicting updates and concurrent operations. Such correctness conditions can not to be handled by quorum-based datastores, especially with weak/eventual consistency settings. Instead, Quorum-based datastores provide users the choice of running applications with weak consistency guarantees

to experience increased availability and partition tolerance [5, 9]),at the risk of undesired anomalies in the data, like negative balance in a bank account or concurrent operations resulting in duplicate values for an unique item.

Many quorum-based distributed data stores, like Cassandra, Riak, and DocumentDB [12, 17, 6], allow users/developers to explicitly declare the desired client-centric consistency [3] setting for an operation. Such systems accept the client-centric consistency settings for an operation in the form of a runtime argument, typically referred to as the *consistency level*. According to consistency level applied, the system waits for coordination among a specific number of replicas containing copies (i.e., versions) of the data item accessed by the given operation [12]. The latency for a given operation depends on the waiting time for the above coordination; hence, in turn, depends on the consistency level applied. For example, a weak consistency level for a read operation in Cassandra [12], like READ ONE, requires only one of the replicas to coordinate successf

Abstract. We investigate the problem of preserving the application level correctness in quorum-based datastores under concurrent application executions, while satisfying any latency threshold specified in the SLA (Service Level Agreement). Consider a sequence of (or a single) operations on a quorum-based datastore invoked from a client application, with a application-level latency threshold specified in the SLA, and the correctness condition specified by the user as post conditions. The observed latency and the correctness of the given operations can be controlled by tuning the client-centric consistency settings of the datastore. We present Consistify, a novel framework that can enable execution of client application on quorum-based datastores with the weakest possible consistency setting, while preserving the correctness, and at the same time satisfying the latency threshold in the SLA. As per our knowledge, Consistify is the first documented work that allows application developers to develop client applications, which can preserve the application level correctness conditions while performing operations on quorum-based datastores, while simultaneously satisfying a given SLA deadline. Consistify achieves the above goals without any dependency on the developer's knowledge of the mechanisms of the underlying datastore, and without any additional declarative language for specifying the application level guarantees. Using benchmark workloads, we experimentally demonstrate that Consistify outperforms (at least doubles the observed throughput) state-of-the-art systems, while also satisfying the given SLA deadlines.

2 Introduction

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Quorum-based datastores [12, 17, 6] often tradeoff support for serializability and transactions (enforced by application of stronger consistency levels) in favor of availability and partition tolerance, hence they can not simultaneously guarantee correctness of application execution and at the same time satisfy latency requirements, especially with concurrent executions [12, 17, 6]. In this context, by correctness we primarily deal with the application level safety properties (liveness is handled internally by the datastore), like anomalies observed by the client due to conflicting updates and concurrent operations. Such correctness conditions can not to be handled by quorum-based datastores, especially with weak/eventual consistency settings. Instead, quorum-based datastores provide users the choice of running applications with weak consistency guarantees to experience lower observed latency, increased availability and partition tolerance [5, 9]),at the risk of undesired anomalies in the data, like negative balance in a bank account or concurrent operations resulting in duplicate values for an unique item. We investigate the possibility of automating the task of determining the weakest consistency level that can preserve the correctness of the given operation, i.e., can produce the correct output as per the semantics of the operation, while at the same time satisfies the SLA threshold for latency. The correctness conditions are application level invariants that are either specified by the users, or are implicitly defined in the application semantics.

2.1 Contributions

We present Consistify, a novel framework that automatically tunes the underlying datastore with the weakest possible consistency settings, under user-specified correctness conditions and SLA deadlines. Internally, Consistify controls the execution order of the operations in client applications, that access quorum-based datastores, and provides automated tuning of the consistency levels for each operation. Thus, Consistify allows client applications to provide any required consistency guarantee (like serializability, causal consistency, eventual consistency, etc.) on the same underlying datastore, without requiring a manual modification of the configuration of the datastore from the application-side. As per our knowledge, Consistify is the first documented work that allows application

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developers to develop client applications, which can preserve the application level correctness conditions while performing operations on quorum-based datastores, also simultaneously satisfying the given SLA deadline. Consistify achieves the above goals without any dependency on the developer's knowledge of the mechanisms of the underlying datastore, and without any additional declarative language for specifying the application level guarantees. While the state-of-the-art systems [19] requires knowledge of programming languages for specifying required application level guarantees, Consistify uses simple first order logic expressions to capture the latency SLA and the correctness condition. Consistify uses lightweight data structures to monitor the dependency relations in the given query sequence, minimizing the usage of local memory and disk. Contrastingly, the state-of-the-art systems either store snapshots or keep local copies of the data, or use the lightweight transaction primitive of Cassandra [12]. The former approach puts additional overhead on the memory and disk usage of the system, while the second approach is unreliable, and causes additional processing delay due to additional Paxos roundtrips [12]. Using benchmark workloads, we experimentally demonstrate that Consistify outperforms (at least doubles the observed throughput) the state-of-the-art systems [19], while also satisfying the given SLA deadlines.

2.2 Correctness Conditions of Example Use Cases

Consistify accepts the correctness conditions for a client application from the users in the form of first order logic relations. Each client application comprises a sequence of *queries* (i.e., storage operations on the underlying datastore, following the standard terminology of storage systems), and the given correctness conditions impose constraints on the values returned by the queries. We illustrate our problem with two example use cases, namely stock trading, and shopping cart applications, and discuss a sample correctness condition for each case. The use case for a shopping cart application may comprise a sequence of queries that perform the operations: 1) browse the catalog, 2) update the cart with selected items, 3) sign in, 4) submit the order, 5) review the invoice, and 4) pay the invoice amount. The correctness condition for the shopping cart application may specify the following constraint regarding the final invoice amount billed for a purchase: $invoice_{amt} = \sum_{k=1}^{item_{types}} n_{item} \times price_{item}$ where n_{item} is the number of items of each type, $price_{item}$ is the unit price of each type of item, $item_{types}$ is the number of the different item types chosen, and $invoice_{amt}$ is the total invoice amount for the purchase. A stock trading application, used for buying/selling of stocks, may perform the following sequence of operations: 1) the investor logs in to the system, 2) the investor chooses buy or sell as the operation type, 3) the investor chooses the name and the number of stocks to trade, 4) system checks the deposit and stock availability for the transaction, 5) if everything is satisfied, system prompts for the order confirmation, 5) once the investor confirms the order, the order detail is recorded in the investor's order history. The correctness condition may state that: $\sum_{stocks} n_{stock} \times price_{stock}^{buy} \leq \sum_{stocks} n_{stock} \times price_{stock}^{selling}$ where n_{stock} are the number stocks being sold,$price_{stock}^{buy}$ is the unit buying price

of a stock, and $price_{stock}^{selling}$ is the unit selling price of a stock, and $\leq$ is the arithmetic operator for the less than equals relation.

3 Design of Consistify

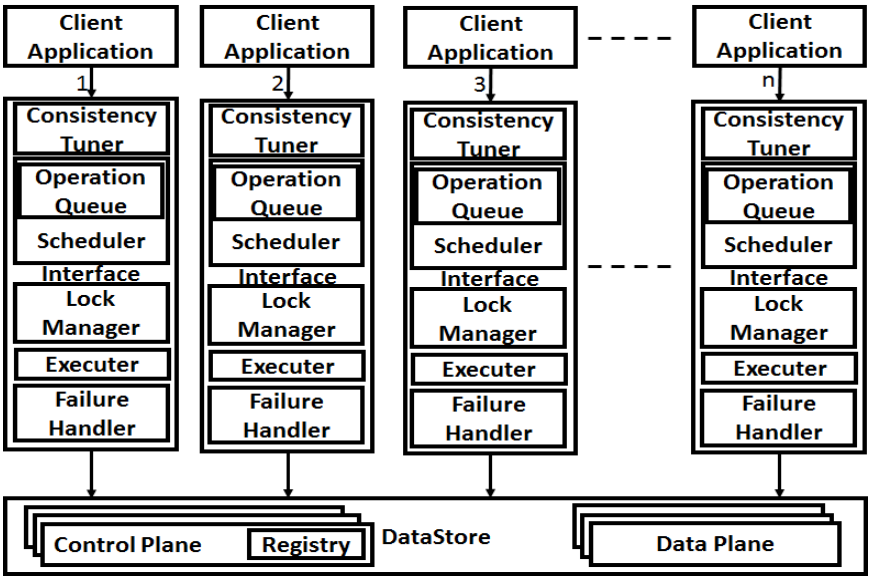


Fig. 1: Architecture of Consistify

Consistify (Figure 1) comprises an interface layer that client applications use to interact with the underlying quorum-based datastore. The interface is implemented as a library module, collocated with the client application. Consistify provides an API comprising methods that can be called from client applications to execute storage operations on the underlying datastore. The above API acts as an abstraction layer that allows application developers to develop client applications that can execute on quorum-based datastores, under given correctness condition and SLA deadline, without knowledge of the mechanisms of the underlying datastore. For each query in the client application, the developer calls a particular method of the Consistify API, passing as arguments the given correctness condition, the SLA deadline, and the values for each key. The *dependency checker* module of the interface extracts the dependency relations in the form of an *UD chain* (i.e., an use-define chain) [1,10] from the query sequence given in the client application.

The interface also comprises a *consistency tuner* module (Figure 1) that determines the weakest possible provably valid consistency level, under the given SLA and correctness conditions. The *operation queue* (Figure 1) buffers the

Algorithm 1 The requestLock Module

procedure REQUESTLOCK(x, q, k, $timeOut$) ▷ Requests to acquire a lock on the key k
Inputs: String x: the unique id of the client that requests the lock,
String q: the query that requests the lock,
String k: the key on which the query requests the lock,
Long $timeOut$ denoting the timeout for the lock request.
returns void
Let the state of the registry $registryState$ be given by the current entries $entry_i$ in the registry for each query $q_{Cl_{id}i}$ invoked by each client Cl_{id} be given as $\langle k,\ q_{Cl_{id}i},\ Cl_{id},\ T^{W}_{Cl_{id}i},\ L^{dep}_{Cl_{id}i},\ L_{Cl_{id}}i^{d}\rangle$
Long $lockState = -999999$, $timestamp = currentTime$, $Booleansuccess = false$
while $timestamp \leq timeOut$ **do**
$lockState = read(lock(k))$ ▷ read the value at column lock for the key k
if $lockState \leftarrow free$ **then**
$lock(k) = x$
$ret = execute(q)$
if $ret == true$ **then**
$removeEntry(x, q, k)$ ▷ Call the module $removeEntry$ to remove the respective registry entry
$removeQueueEntry(x, q, k)$ ▷ Call the module $removeQueueEntry$ to remove the respective entry from the operation queue
end if
else
wait;
end if
end while
if $success \leftarrow false$ **then**
$resetRegistryEntry(x, q, k)$ ▷ Call the module $resetRegistryEntry$ to mark the query as filed and setting it for a retry in next scheduling cycle
$lock(k) = free$
end if
end procedure

queries that require causality or serializability. Consistify partitions the underlying datastore into a dataplane (Figure 1), for storing the actual dataset, and a control plane, which maintains a *registry* object. In the case of requirement of serializability, the *scheduler* module checks if there exists a conflicting query that accesses the same key, In case of existence of a conflicting query, the query registers its intent to access the key in question by writing an entry $entry_k$ to the registry. $entry_k$ is a tuple $\langle k,\ q_{Cl_{id}i},\ Cl_{id},\ T^{W}_{Cl_{id}i},\ L^{dep}_{Cl_{id}i},\ L^{d}_{Cl_{id}i},\ STATUS\rangle$ comprising: 1) the name of the key k, 2) an unique id Cl_{id}, identifying the identity of the client application invoking the query $q_{Cl_{id}i}$ in question, 3) the query statement $q_{Cl_{id}i}$, 4) the waiting time of $T^{W}_{Cl_{id}i}$ of the query, initialized with the

timestamp difference T - $T^{inv}_{Cl_{id}i}$, where $T^{inv}_{Cl_{id}i}$ is the timestamp of the invocation of the query, and T is the current timestamp, 5) $L^{dep}_{Cl_{id}i}$, which is the sum of the estimated latency of all the queries dependent on $q_{Cl_{id}i}$, given as $\sum_{i=1}^{n} L^{Est}_{Cl_{idi}}$, where n = the number of queries dependent on $q_{Cl_{id}i}$, 6) the current deadline $L^{d}_{Cl_{id}i}$ of the client application, initialized with the latency threshold L_{SLA} specified in the SLA for the given application, and 7) a flag *STATUS* that represents whether the query has already been scheduled, i.e., takes values ON or OFF. From the time of invocation till the completion of execution of the client application, the timestamps for the waiting time and the current deadline in $entry_k$ are regularly updated as: $T^{W}_{Cl_{id}i} = T$ - $T^{W}_{Cl_{id}i}$, and $L^{d}_{Cl_{id}} = L^{d}_{Cl_{id}}$ - $(T$ - $T^{inv}_{Cl_{id}})$, respectively. The scheduler module schedules the queries waiting in the registry based on the entries $entry_k$. Once the conflict has been cleared, the control is passed on to the *lock manager* module. It enables the query to acquire a lock on the concerned key by setting the value of the lock column in the datastore to an unique id, identifying the given query and the client application. Algorithm 3 is the algorithm for our lock manager module implementation.

3.1 Consistency Tuner: Determining Provably Valid Consistency Settings

For the given quorum-based store [12, 17, 6], consider that *Rep* is the given replication factor. For a given query $q_{Cl_{id}i}$ performed on the quorum based stores with a consistency level corresponding to the nominal attribute $C_{Cl_{id}i}$, $frac \times 1/Rep$ number of nodes must respond with acknowledgement, where the parameter *frac* varies from 1 for consistency level $C_{Cl_{id}i}$ = ALL to *Rep* for $C_{Cl_{id}i}$ = ONE, in Cassandra. The queries that do not use or define the keys in the correctness condition, can be concurrently executed with eventual consistency settings, i.e., with the weakest consistency levels ANY/ONE in Cassandra. Such queries execute with the weakest consistency level, and they execute concurrently with other queries. Hence, these queries don't affect the SLA deadline. Hence, the tuner considers the SLA deadline only for queries that require causality/serializablilty guarantees. Consider that $frac_i \times 1/Rep$ and $frac_j \times 1/Rep$ are the number of nodes that must respond corresponding to the given consistency levels $C_{q_{Cl_{id}i}}$ and $C_{q_{Cl_{id}j}}$ for queries $q_{Cl_{id}i}$ and $q_{Cl_{id}j}$, respectively, where $1 \leq frac_i \leq Rep$ and $1 \leq frac_j \leq Rep$ [12, 17, 6]. The condition for the pair of queries $q_{Cl_{id}i}$ and $q_{Cl_{id}j}$ to execute under causal guarantee demands the following: If a write query $q_{Cl_{id}j}$ defines a variable *var* that is used by the read query $q_{Cl_{id}i}$, then consistency levels $C^{mat}_{q_{Cl_{id}i}}$ and $C^{mat}_{q_{Cl_{id}j}}$ must be such that $frac_i \times 1/Rep + frac_j \times 1/Rep \geq Rep$. The above rule is the necessary condition for reading correct writes in quorum-based stores [12, 17, 6]. The above condition ensures that the quorum of replicas accessed for the read and write overlaps, thus guaranteeing that the correct value gets read. For example, $C^{mat}_{q_{Cl_{id}j}}$ = ONE implies $frac_j \times 1/Rep = 1$. Hence, for the above condition to hold, it requires that $frac_i \times 1/Rep \geq Rep - 1$, which in turn requires that $frac_i \geq 1$. The only consistency level for which $frac_i \geq 1$ holds is ALL, hence $C^{mat}_{q_{Cl_{id}i}}$ must be ALL for satisfying the condition U.

4 Use Define Chains

We refer to a given query to have *defined* a given variable (i.e., key), if it is the last write query that accessed this variable prior to the given query. Similarly a given query is said to *use* a given variable, if: 1) in the case of a read query, it is the first query to have read the concerned variable defined in a prior query 2) in the case of a write query, it is the first query to update another variable with the value of the concerned variable defined by a prior query. Use define chains (UD) [1, ?] can be used to determine: 1) the query that uses (*USES*) a particular variable defined by a given query, and 2) the query which defines (*DEF*) a variable that is being used by the given query. Consistify applies UD chains to identify dependency among the individual queries in a given query sequence. UD chains are based on functions *DEF* and *USES* which are defined as: if the variable *var* used in a given query $q_{Cl_{id}i}$ is defined by a prior query $q_{Cl_{id}j}$ invoked from a client application Cl_{id}, $DEF(var, q_{Cl_{id}i}) = q_{Cl_{id}j}$, and $USES(var, q_{Cl_{id}j}) = q_{Cl_{id}i}$. The above dependency is used to derive the safety/correctness properties that need to be satisfied for safely executing a given query on the system. The UD chains for the given query sequence are developed as follows.

$\mathsf{DEF}(\mathsf{x}, q_{i1}) = \phi$; $\mathsf{USES}(\mathsf{x}, q_{i1}) = \phi$;
$\mathsf{DEF}(\mathsf{y}, q_{i2}) = \phi$; $\mathsf{USES}(\mathsf{y}, q_{i2}) = \phi$;
$\mathsf{DEF}(\mathsf{sum}, q_{i3}) = q_{i3}$; $\mathsf{USES}(\mathsf{sum}, q_{i3}) = q_{i4}$;
$\mathsf{DEF}(\mathsf{z}, q_{i4}) = q_{i4}$; $\mathsf{USES}(\mathsf{z}, q_{i4}) = q_{i5}$;
$\mathsf{DEF}(\mathsf{z}, q_{i5}) = q_{i4}$; $\mathsf{USES}(\mathsf{z}, q_{i5}) = \phi$;

4.1 The Consistify Scheduler

Firstly, the scheduler performs schedulability analysis for the query sequence comprising the given client application under the given SLA, and the correctness condition. The queries requiring eventual consistency can execute concurrently with the weakest consistency level, producing lowest latency. Hence, the aggregate completion time of these queries is computed as the latency of the query with the maximum estimated latency. On the other hand, the overall completion time for queries requiring causality/serializability is approximately estimated as the sum of the estimated latencies of the queries. Hence, the given application is schedulable if the SLA equals or exceeds the maximum of the following estimated times: 1) the maximum of the estimated latencies of the queries requiring eventual consistency, and 2) the sum of the estimated latency for the queries requiring serializability or causality. If the application is schedulable, the scheduler first buffers the concurrent queries that have registered their intent to execute on the datastore by making entries in the registry. For concurrent queries from multiple clients trying to access a given lock, the scheduler checks the registry entries to estimate the following quantities: 1) the waiting time $T^W_{Cl_{id}i}$ for each query, and 2) the aggregate latency $L^{dep}_{Cl_{id}i}$ for the queries that are dependent on a given query. The scheduler then determines which client has the least amount of time left to satisfy its current deadline $L_{Cl_{id}}{i^d}$. Thus, it selects the query $q_{Cl_{id}i}$

Algorithm 2 The Consistify Fair Scheduler

procedure SCHEDULER(*registryState*) ▷ the Fair Scheduler which schedules a query from the registry to acquire a lock on the given query
returns void
Let the state of the registry *registryState* be given by the current entries $entry_i$ in the registry for each query $q_{Cl_{id}i}$ invoked by each client Cl_{id} be given as $\langle k,\ q_{Cl_{id}i},\ Cl_{id},\ T^{W}_{Cl_{id}i},\ L^{dep}_{Cl_{id}i},\ L_{Cl_{id}}i^{d}, STATUS\rangle$
$j = 0,\ min = 0$;
if $checkSchedulability \leftarrow true$ **then**
while $j \leq size(registryState)$ **do**
$\langle k,\ q_{Cl_{id}i},\ Cl_{id},\ T^{W}_{Cl_{id}i},\ L^{dep}_{Cl_{id}i},\ L_{Cl_{id}}i^{d}, STATUS\rangle = \text{read}(entry_j)$;
if $STATUS \not\leftarrow ON \wedge min \geq L_{Cl_{id}}i^{d} - T^{W}_{Cl_{id}i} - L^{dep}_{Cl_{id}i}$ **then**
$min\ =\ L_{Cl_{id}}i^{d} - T^{W}_{Cl_{id}i} - L^{dep}_{Cl_{id}i}$
$x = Cl_{id}$;
$q = q_{Cl_{id}i}$
$write(entry_j, \langle k,\ q_{Cl_{id}i},\ Cl_{id},\ T^{W}_{Cl_{id}i},\ L^{dep}_{Cl_{id}i},\ L_{Cl_{id}}i^{d}, ON\rangle)$;
else
j++;
end if
end while
requestLock(x,k,q,timeOut); ▷ Call the module requestLock to request a lock on the key k with a preconfigured *timeOut*
end if
end procedure

which produce the minimum value for the expression $L_{Cl_{id}}i^{d} - T^{W}_{Cl_{id}i} - L^{dep}_{Cl_{id}i}$, and marks $q_{Cl_{id}i}$ by setting the value of *STATUS* column in the registry to ON. The selected query then requests to acquire the lock on the concerned key. When the lock is free, the query acquires the lock by setting the lock column to its unique client id. Upon completion of the query execution, the lock is freed, and the corresponding entries in the registry and the operation queue are removed. The scheduler is fair, i.e., it provides each query in the registry the chance for serialized execution by acquiring locks on the datastore in a fair manner, where no query is starved indefinitely beyond a predefined threshold.

4.2 Failure Handling

State-of-the art quorum-based stores [12, 17, 6] return error messages to the console during failure of execution of queries, but depends on the developers to take action with respect to each kind of failure. Consistify relieves the developers from the task of explicitly handling failures, which requires the developers to have the ability to identify the various error messages (and the causes of the errors) just from their names. The Consistify failure handler collects and interprets the error messages, and ensures correctness of the application despite such failure, while relaxing on the SLA deadline in extreme cases. The failure handler only handle

Algorithm 3 The requestLock Module

procedure REQUESTLOCK(x, q, k, $timeOut$) ▷ Requests to acquire a lock on the key k
Inputs: String x: the unique id of the client that requests the lock,
String q: the query that requests the lock,
String k: the key on which the query requests the lock,
Long $timeOut$ denoting the timeout for the lock request.
returns void
Let the state of the registry $registryState$ be given by the current entries $entry_i$ in the registry for each query $q_{Cl_{id}i}$ invoked by each client Cl_{id} be given as $\langle k,\ q_{Cl_{id}i},\ Cl_{id},\ T^{W}_{Cl_{id}i},\ L^{dep}_{Cl_{id}i},\ L_{Cl_{id}}i^{d}\rangle$
Long $lockState = -999999$, $timestamp = currentTime$, $Booleansuccess = false$
while $timestamp \leq timeOut$ **do**
$lockState = read(lock(k))$ ▷ read the value at column lock for the key k
if $lockState \leftarrow free$ **then**
$lock(k) = x$
$ret = execute(q)$
if $ret == true$ **then**
$removeEntry(x, q, k)$ ▷ Call the module $removeEntry$ to remove the respective registry entry
$removeQueueEntry(x, q, k)$ ▷ Call the module $removeQueueEntry$ to remove the respective entry from the operation queue

end if
else
wait;
end if
end while
if $success \leftarrow false$ **then**
$resetRegistryEntry(x, q, k)$ ▷ Call the module $resetRegistryEntry$ to mark the query as filed and setting it for a retry in next scheduling cycle
$lock(k) = free$
end if
end procedure

failures for queries that require causality or serializability guarantees, since by design (Section 3) only those queries affect the correctness condition. It stores the last value of the key updated by the query in a temporary variable. If the query fails with a replica unavailability exception or a read timeout (Consistify does not addresses Byzantine failures), the failure handler removes the corresponding entry from the registry, rolls back any update made by that query, restores the old value of the respective key from the temporary variable. The query is then re-inserted into operation queue, and waits for execution. However, by enforcing retry of queries on failures, the SLA deadlines may be violated in certain cases at the cost of correctness of execution. If the application fails to satisfy the cor-

rectness condition, the updates due to the serializable queries are rolled back, the concerned keys are restored to their old values, and a message is sent to the user informing that the application is being retried. If the SLA is violated, the interface sends a failure message, along with the delay by which the SLA was overshoot. It also asks the user if the user accepts the results despite the SLA violation, or if the application should be retried. In case of the latter choice, the interface rollbacks the updates, and re-inserts the queries in the operation queue.

5 Estimating the Latency for an Applied Consistency Level

The verifier module of Consistify determines the weakest possible consistency level to satisfy the latency threshold of the SLA. To perform this task, Consistify must estimate the latency for a given query performed with each possible consistency level on the given datastore. The latency observed for a given query performed with a given consistency level varies with respect to the replication factor of the datastore, the network conditions of the cluster. In the absence of a mathematical relation binding the applied consistency level to latency, the latency must be estimated either with training or approximated with benchmark workloads. The approach of using training requires large training data and has the pitfall of overfitting. Instead, Consistify uses 95 percentile latency estimates obtained by running YCSB [7] benchmark workloads with each possible consistency level on clusters comprising same number of nodes and replication factor.

6 Putting the Pieces Together: How Consistify Works

```
q1: read(x); //reads the value at x
q2: read(y); //reads the value at y
q3: sum=x+y; //adds the values x and y and stores in temporary
    variable sum
q4: write(z,sum); //writes sum to the key z
q5: read(z); //reads the value at z
```

Fig. 2: Example Query Sequence

We illustrate how Consistify handles the given problem of consistency tuning on a quorum-based datastore with the running example in Figure 2, comprising a sequence of queries q_1 to q_5 invoked from a client application Cl_{id}, and a latency threshold SLA for the application specified in the SLA. The datastore is

initialized as follows: the value 1 stored at the key x, 2 at y, and 4 at z. Consider that the business logic for the above application code require that the observed output, i.e., the value returned by the query q_5, is 3. Thus, the correctness condition for the above application is that the observed output must be 3, i.e., $z = 3$. We determine the weakest possible consistency level that can be applied for each query in the above query sequence, and the required execution order of the given query sequence, such that the above correctness condition is preserved. We use the notation $q_{Cl_{id}i}$ to denote the invocation of a query q_i from a client Cl_{id}.

Once invoked, the client application calls the dependency checker module of Consistify (Figure 1), which is collocated with the client. The dependency checker extracts the dependency relations among the queries in the client application in the form of an UD chain. The UD chains for the given query sequence are developed as follows.

$\mathsf{DEF}(\mathsf{x}, q_{i1}) = \phi$; $\mathsf{USES}(\mathsf{x}, q_{i1}) = \phi$;
$\mathsf{DEF}(\mathsf{y}, q_{i2}) = \phi$; $\mathsf{USES}(\mathsf{y}, q_{i2}) = \phi$;
$\mathsf{DEF}(\mathsf{sum}, q_{i3}) = q_{i3}$; $\mathsf{USES}(\mathsf{sum}, q_{i3}) = q_{i4}$;
$\mathsf{DEF}(\mathsf{z}, q_{i4}) = q_{i4}$; $\mathsf{USES}(\mathsf{z}, q_{i4}) = q_{i5}$;
$\mathsf{DEF}(\mathsf{z}, q_{i5}) = q_{i4}$; $\mathsf{USES}(\mathsf{z}, q_{i5}) = \phi$;

The interface performs schedulability analysis (Section 4.1) for the given client application under the given SLA, and the correctness condition. Then, it determines the queries that do not access the keys referred to in the correctness conditions, i.e., q_1, and q_2. Eventual consistency is sufficient for these queries; hence they are directly passed on to the verifier, bypassing the operation queue. The verifier determines that ANY/ONE read-write consistency levels are the weakest possible valid consistency levels for q_1, and q_2 under the given SLA. A given query can execute only if there does not exist an entry in the registry, comprising a conflicting query (from another client) that is currently accessing the same keys. Once the conflict for each of the queries q_1 and q_2 has been cleared, they are concurrently executed over the datastore, with the consistency levels predicted by the verifier.

From the UD chain and the given correctness condition, the dependency checker determines that the queries q_3, q_4, and q_5 require pairwise serializability. Hence, q_3, q_4, and q_5 are inserted into the operation queue (Figure 1). The scheduler (Figure 1) first writes an entry for q_3. At an instant of time, determined by the scheduling algorithm [5], q_3 is chosen among the registry entries. The scheduler sets the *STATUS* column of the registry to ON, and calls the

[5] The scheduler (refer algorithm 2) regularly updates the deadlines of the queries in the registry with respect to the SLA deadline, the invocation time, and the current timestamp. $L^d_{q_{Cl_{id}3}}$ and $L^d_{q_{Cl_{id}4}}$ are the current deadlines for the query $q_{Cl_{id}3}$ and $q_{Cl_{id}4}$. For concurrent queries from multiple clients trying to access a given lock, the scheduler checks the registry entries to determine the waiting time $T^W_{Cl_{id}i}$ for each query. It also estimates the aggregate latency $L^{dep}_{Cl_{id}i}$ for the queries that are dependent on a given query. The scheduler then determines which client has the least amount of time left to satisfy its current deadline $L_{Cl_{id}}i^d$, i.e., it selects the

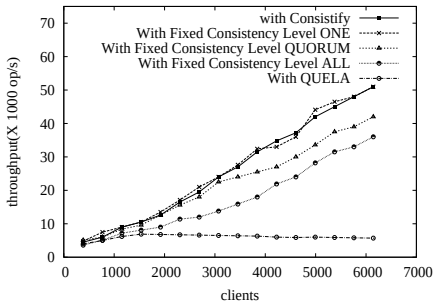
requestLock algorithm for requesting a lock on *sum*. setting the lock column to an unique id, identifying q_3 and the client application.

Once q_3 acquires the lock, it calls the verifier (Figure 1) to determine the weakest possible consistency level. The verifier uses the weakest precondition $P_{q_{Cl_{id}3}}$ (Section 3.1) to determine the set of weakest matching consistency levels $C^{mat}_{q_{Cl_{id}3}}$ and $C^{mat}_{q_{Cl_{id}4}}$, that satisfies the condition $frac_3 \times 1/Rep + frac_4 \times 1/Rep \geq Rep$. The verifier must choose a pair of consistency levels from the above matching set, such that resultant latency of q_3 and q_4 satisfies the respective deadlines, estimated with respect to the SLA, i.e., $L^j_{q_{Cl_{id}}3} \leq L^d_{q_{Cl_{id}}3}$ and $L^j_{q_{Cl_{id}}4} \leq L^d_{q_{Cl_{id}}4}$. Then it executes on the datastore with the consistency level predicted by the verifier. Upon completion of execution, it resets the lock column for *sum* to free and removes the corresponding entry from the registry. The failure handler (Section 4.2) listens for any error message returned by q_3. If q_3 fails with an exception like unavailability of replicas, failure handler rollbacks the effects of q_3 by restoring the value of *sum* to its old value It re-inserts q_3 to the operation queue, and updates the current deadline of q_3 with the delay due to the failed query. Once q_3 is removed from the registry, q_4 is released from the queue, and q_4 writes an entry the registry. According to the scheduling algorithm (Algorithm 2) requests for the lock to the key z at a particular instant of time. Once the lock for z is free, q_4 acquires the lock on z, and executes with the consistency level predicted by the verifier. The verifier uses the weakest precondition $P_{q_{Cl_{id}}4}$ to determine the weakest matching consistency levels $C^{mat}_{q_{Cl_{id}}4}$ and $C^{mat}_{q_{Cl_{id}}5}$, such that $frac_4 \times 1/Rep + frac_5 \times 1/Rep \geq Rep$, and $L^j_{q_{Cl_{id}}4} \leq L^d_{q_{Cl_{id}}4}$ and $L^j_{q_{Cl_{id}}5} \leq L^d_{q_{Cl_{id}}5}$. Once q_4 finishes execution, the scheduler sets the lock column to free and removes the entry from the registry. Finally, q_5 writes to the registry, and acquires the lock on z. It gets executed with the weakest possible consistency level from the matching set $C^{mat}_{q_{Cl_{id}}5}$, satisfying the SLA and producing the desired output, i.e., $z = 3$. If the application fails to satisfy the correctness condition, the updates due to the queries q_3, q_4, and q_5 are rolled back. The keys *sum* and z are restored to their old values, and a message is sent to the user informing that the application is being retried. The application retries q_3, q_4, and q_5 in the order of their invocation, inserting q_3 in the operation queue first. If the SLA is violated, the interface sends a failure message, along with the delay by which the SLA was overshoot. Consistify also asks the user if the user accepts the results despite the SLA violation, or if the application should be retried. In case of the latter choice, the interface rollbacks the updates due to q_3, q_4, and q_5, and inserts the query q_3 in the operation queue.

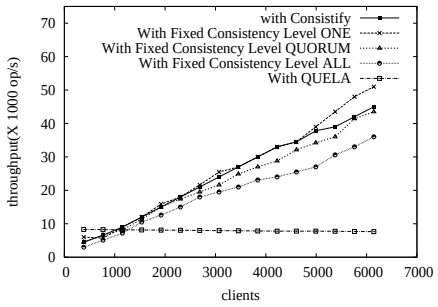
7 Implementation

The Consistify interface is implemented as a Java middleware, using connection and accessor methods provided by the Cassandra driver core version 2.1.6

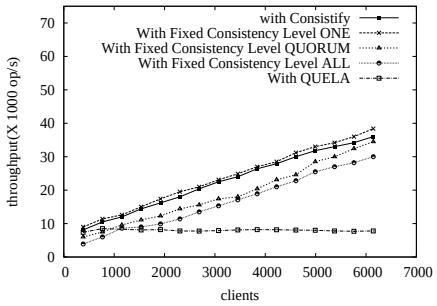
query which produce the minimum value for the expression $L_{Cl_{id}}i^d - T^W_{Cl_{id}i} - L^{dep}_{Cl_{id}i}$, to request for the lock (Section 4.1).



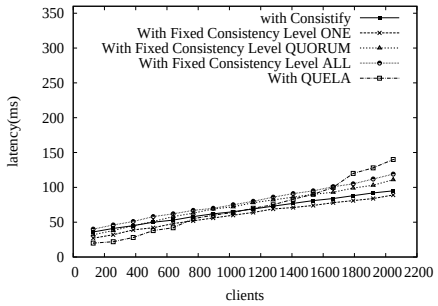
(a) Throughput vs No of Clients for Stocking Trading Application



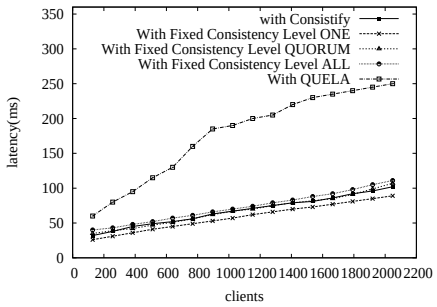
(b) Throughput vs No of Clients for Shopping Cart Application



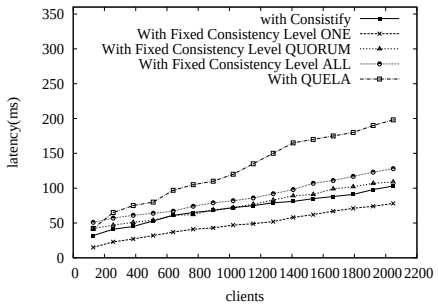
(c) Throughput vs No of Clients for Retail Store Application



(d) Latency vs No of Clients for Stock Trading Application

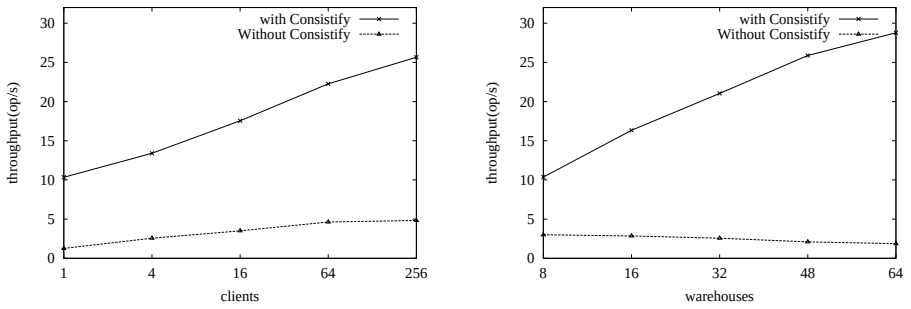


(e) Latency vs No of Clients for Shopping Cart Application



(f) Latency vs No of Clients for Retail Store Application

Fig. 3: Results With Consistify vs those With QUELA and those With Manually Chosen Fixed Consistency Level



(a) Throughput vs No of Clients for TPC-C

(b) Throughput vs No of Warehouses for TPC-C

Fig. 4: Results With TPC-C With and Without Consistify

maintained by the Datastax community. Consistify uses 95 percentile latency estimates obtained by running YCSB [7] benchmark workloads with each possible consistency level on clusters comprising same number of nodes and replication factor. Consistify provides the developers with a high level API comprising a group of accessor methods that can be used to execute different storage operations on a quorum-based datastore while hiding the internal syntactic details of the underlying datastore. The Consistify API allows application developers the flexibility of developing the application without requiring them to possess any knowledge of the internal mechanisms of the underlying datastore. The developer passes the correctness condition and the SLA deadline to the API methods in the form of a first order logic statements. The Consistify interface parses the above statements, and determines the weakest possible consistency levels for the given sequence of operations. Applying the above consistency levels, the developer calls the accessor methods from the API to execute the given sequence of operations on the underlying datastore. The open source codebase for the Consistify interface can be found in the github repository: `https://github.com/ssidhanta/Consistify`. Also, we integrated the Consistify interface as an extension over PY-TPCC, a widely used [**?**] state-of-the-art open source python implementation of the TPC-C benchmark. The codebase for our TPC-C prototype can be found in the github repository: `https://github.com/ssidhanta/py-tpcc-master`.

8 Evaluation

We evaluate the performance of Consistify over Cassandra [12], one of the most widely used quorum-based datastore, with different benchmark client applications. We run our experiments on a geo-replicated testbed comprising 3 Amazon [6] ec2 c3.2xlarge instances, spread out across 2 ec2 regions, running Apache Cas-

[6] Consistify is supported by an AWS in Education Research Grant award.

sandra 2.1.6 with a replication factor of 3, loaded on top of Ubuntu 13.10. Following the state-of-the-art [19], we discuss the results of experiments performed with three benchmark applications - stock trading, shopping cart, and online retail store, The client applications are invoked from remote m3 ec2 instances running Ubuntu 13.10, which are not collocated with the servers. Figures 3(a), 3(b), 3(c), 3(d), 3(e), and 3(f) present the throughput (in terms of operations per second) and latency (in milliseconds) measures against varying number of clients, with consistency levels chosen with Consistify, and with manually chosen fixed consistency levels, respectively. The results indicate that Consistify succeeds in producing increased observed throughput and lower observed latency, in contrast with fixed manually chosen consistency settings (like ONE, QUORUM, ALL in Cassandra). This can be attributed to the application of the weakest possible consistency setting in each case. With the exception of Quela [19], Consistify is the only system to allow client applications to enforce correctness conditions and SLA deadlines on top of quorum-based datastores. The results with the benchmark applications demonstrate that Consistify outperform the state-of-the-art, in terms of both obtained throughput and observed latency. In fact, the observed throughput with Consistify is at least double that reported by Quela, and the observed latency is also consistently less with Consistify [19]. On top of that, Consistify successfully satisfies imposed SLA deadlines (5 seconds per application), while Quela does not consider SLAs at all.

We also present the results with an open source implementation of the TPC-C benchmark over Apache Cassandra 2.1.6. Figure 4(a) presents the throughput measures (operations per second) against varying number of clients, while Figure 4(b) presents the throughput against varying number of warehouses, with and without consistency levels chosen with Consistify. Apart from [?], Consistify is the first work that provides documented results of running TPC-C benchmark workloads over a quorum-based datastore, instead of a relational database. Figures 4(a) and 4(b) show that Consistify clearly outperforms the state-of-the-art [?].

9 Related Work

In practice eventual consistency is preferred over strong consistency in scenarios where the system must maintain availability during network partitions [3, 21], or when the application is latency-sensitive and able to tolerate occasional inconsistencies [5, 9]).A large body of research deals with the problem of supporting various forms of stronger-than-eventual consistency in scalable storage systems and databases. The state machine replication paradigm achieves the strongest possible form of consistency by physically serializing operations [13]. Lamport's Paxos protocol is a quorum-based fault-tolerant protocol for state machine replication [14]. Mencius improves upon Paxos by ensuring better scalability and higher throughput under high client load using a rotating coordinator scheme [16]. A number of scalable fault-tolerant storage systems have been constructed using variations on Paxos [18, 4, 11, 8].

Relatively few systems [22, 20, 2, 19] provide mechanisms for fine-grained control over consistency. Pileus and Tuba [20, 2] are the only systems that come close to providing fine grained consistency tuning using SLAs. But, instead of predicting, these systems perform actual trials on the system, and select the consistency level corresponding to the SLA row that produces minimum resultant utility, based on the trial outcomes. The trial-based technique can produce unreliable results due to the unpredictable parameters like network conditions and workload that affect the observed latency and staleness. Thus, predictions based on the outcomes of the trial phase may be unsuitable in the actual running time of the operation. Sivaramakrishnan et. al. [19] use a static analysis approach to determine the weakest consistency level that satisfies the correctness conditions declared in the contract. It requires the users to have knowledge of a declarative language for specifying the contract, and to accurately specify the correctness rules in the contract. Also, it does not explicitly consider the latency as an SLA parameter, and cannot dynamically adapt to varying workload and network state. Li et. al. [15] applies static analysis for automated consistency tuning for relational databases.

10 Conclusions

We presented Consistify, a novel framework that provides automated consistency tuning of quorum-based datastores for execution of client applications under a given correctness condition and SLA deadline. Consistify tunes the underlying datastore with the provably valid weakest possible consistency settings under the given SLA deadline and the correctness condition. Consistify provides an abstraction layer that allows application developers to develop client applications on top of a quorum-based datastore, without requiring the developers to have any expertise of the mechanisms of the underlying datastore. Consistify allows the client applications to work under different consistency guarantees, determined from the user-specified correctness condition, on top of the same underlying datastore, under given SLA deadline. The Consistify interface upgrades the datastore such that it is possible to enforce the above correctness conditions on the given datastore, without additional memory or storage overhead for maintaining to local copies or snapshot. Experimental results demonstrate that Consistify exceeds the observed performance of the state-of-the-art systems. In contrast with the current state-of-the-art, Consistify can work under a given SLA deadline, in addition with satisfying a given correctness condition.

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