Evolving NoSQL Databases Without Downtime

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Abstract—NoSQL databases like Redis, Cassandra, and MongoDB are increasingly popular because they are flexible, lightweight, and easy to work with. As usual, applications that use these databases evolve over time, sometimes necessitating (or preferring) a change to the format of the data. The problem we address in this paper is: How can we support the evolution of high-availability applications and their NoSQL data on-line, without excessive delays or interruptions? This requires orchestrating the changes among the database and all the clients accessing it, and is challenging to implement in a safe and general-purpose manner in the presence of backward-incompatible data-format changes. We present KVolve as a solution to this problem. KVolve permits a developer to submit an upgrade specification, written in a domain-specific language we developed that defines how to transform existing data to the newest version. This transformation is applied lazily, as applications interact with the database, thus avoiding long pause times. We demonstrate performing updates to JSON values involving adding, deleting, and updating, and modifying JSON fields, and also demonstrate modifications to the key names. We find that our system has only around 4.95%-8.6% overhead in general use cases, and that the pause time during lazy updates is less than transforming the database all at once.

I. INTRODUCTION

NoSQL databases, such as Redis [1], Cassandra [2], and MongoDB [3], are increasingly the go-to choice for storing persistent data, dominating traditional SQL-based database management systems [4], [5]. NoSQL databases are often organized as key-value stores, in that they provide a simple key-based lookup and update service (i.e., “no SQL”). While these databases do not provide a formal language for specifying a schema, applications often attach meaning to the format of the keys and values stored in the database. Keys are typically structured strings, and values are represented according to various possible formats [6], e.g., as Protocol Buffers [7], Thrift [8], Avro [9], or JSON [10] objects.

Applications that use NoSQL databases will evolve over time, just as any application will, and preferred evolutions may require updating the format of DB-resident data. Such updates may include the adding fields to or deleting fields from objects, splitting objects so they are mapped to by multiple keys rather than a single key, renaming of keys or value fields, and so on. When changes are not compatible with the old version of an application, a straightforward way to deploy them in the field would be to shut down the running applications; migrate each affected object in the database from the old format to the new format; and then start the new versions of the applications.

Performing these changes online is more challenging. The parsers for Thrift, Protocol Buffers, and Avro provide some support for format changes e.g. by skipping unknown fields or by attempting to translate data from the writer schema into the reader schema [11]. This leaves the task of updating each object in the database (e.g., by iterating over all of its keys [12]). For large amounts of data, this can create an unacceptably long pause. For example, we found that updating 200,000 keys could take as long as a full minute on our benchmarking setup. Developers could avoid shutting down the application by making the new format backward-compatible with the old format, but this would impose a significant constraint on the future evolution of the application. It may also be possible to grant applications read-only access to the old database while the migration takes place, but applications that have even occasional writes will suffer.

One way to avoid downtime and database locking is to migrate data lazily. When the application accesses an object in the old format, the object is converted to the new format on-the-fly. Thus, the only update-time pause is due to shutting down and restarting the application—the far longer pause due to migrating the data is now amortized over the new version’s execution, causing slower queries immediately after the update but no full stoppage. In practice, developers are often advised to write code that expects data in both old and new formats and to implement the lazy migration code in the application logic [13], [14], [15], [16]. This approach adds burden on the programmer and results in code that mixes application and format-maintenance logic. Moreover, since there is no guarantee that all data will ultimately be migrated, this migration code expands with each new application version, becoming more confusing and harder to maintain.

This paper presents KVolve as a solution to the problem of evolving a NoSQL database. KVolve migrates data as it is accessed, minimizing down-time, but requires almost no changes to applications. Instead, migrations happen transparently, in a wrapper that interposes between the normal lookup and update calls. The wrapper attaches a version identifier to the key of each updated and looked-up value. If a query finds no current-version key, the wrapper checks for, and migrates, any earlier version it finds. Pleasantly, KVolve’s wrapper-based approach requires no changes to Redis itself.

KVolve supports Redis databases containing JSON objects, as we have found JSON to be a popular choice. Migrations are defined in a simple domain-specific language we designed which supports changes that seem common in practice, such

\(^1\)KVolve stands for “Key-Value store evolution”.
as adding to or modifying the format of JSON objects, and modifying the structure of keys. While the details of both NoSQL databases and structured values (JSON vs. Proto Bufs, etc.) differ, we believe the main ideas we present here should transfer to these other settings.

Experiments with our implementation show that KVolve imposes a small overhead during normal operation. Using a benchmark that repeatedly queries the database (the worst case as far as application performance is concerned), we observe between 5 and 9% overhead. We also find that laziness is a significant benefit when an update first takes place: rather than imposing a long pause while data is migrated, clients are allowed to immediately continue querying after restarting at the new version.

In summary, we make the following contributions:

- We define a general approach to updating data formats in NoSQL databases lazily. For large databases, this approach gives the appearance of an instant update, as the applications can start using the new data format without delay, and amortizes the cost of migration over the normal execution. Additionally, this approach does not limit the client-side interactions (e.g., to read-only execution) and requires very few changes to applications as most work piggybacks on normal operations. (Section II.)
- We define a new domain-specific language for simplifying the specification of data migrations. This provides a separation of concerns between the application logic and the data-format maintenance. We support a variety of changes, including backward incompatible ones. (Section III.)
- Our implementation on top of the Redis NoSQL database requires no changes to Redis itself: it is implemented entirely as wrappers around application-level actions. (Section IV.)
- Experiments show that KVolve adds only a small overhead during normal operation, with some performance degradation during the lazy update rather than a full stoppage. (Section V.)

To the best of our knowledge (see Section VI), KVolve represents the first general-purpose solution to the problem of evolving a NoSQL database without downtime. We plan to make our code freely available.

II. OVERVIEW

This section presents an overview of KVolve, describing its various pieces and how the fit together using a simple example.

A. Background on Redis and NoSQL databases

NoSQL databases are distinguished from traditional relational database management systems (RDBMSs), in supporting a very simple, lightweight interface. Our focus is on a variant referred to as key-value stores which, as the name implies, focus on mapping keys to values. We chose to work with the key-value store Redis [1], one of the most widely used key-value databases [17]. The main operations in Redis, in particular, are: GET $k$, which returns the value $v$ to which $k$ maps in the database (or “none” if none is present); and SET $k$ $v$, which adds (or overwrites) the mapping $k \rightarrow v$ in the database. Redis supports variations of these operations (e.g., setting values only if no prior version exists, or defining mappings that will time out), and additional datastructures, like sets. KVolve supports most of the basic Redis commands, but does not yet support all of them, as discussed in Section IV-D.

Many applications store string values that adhere to formats such as JSON [10], Avro [9], or Protocol Buffers (“Proto Bufs”) [7]. In this paper, we focus on Redis databases that store JSON objects. JSON defines four primitive types: numbers, strings, booleans, and null. It also defines two container types: arrays, which are an ordered list of values of the same JSON type; and objects, which are an unordered collection of values of any JSON type, with field labels. Our basic approach should apply to other formats as well, and it would arguably be easier to do so, as Avro and Proto Bufs also define a notion of schema that could be analyzed to understand the effect of a change.

A common programming practice for key-value stores is the use of namespaces, which conceptually divide up the kinds of objects stored in the database. Redis does not provide native support for namespaces, but rather advises their use by convention: Keys should have the format $n:k$ where $n$ identifies the namespace, and $k$ identifies the proper key name. The assumption is that objects in namespace $n$ will all have the same type. Of course, $n$ might be further partitioned into sub-namespaces, as required.

B. Schema change example

As an example, consider an on-line store (borrowed from an example by Sadalage and Fowler [13]). Such an application may store purchase orders in its database. Keys have the format order:$n$ where order is the namespace, and $n$ is a unique number, representing an invoice number. Such keys map to values that describe a purchase, formatted as JSON as shown in Figure 1a.

Suppose we wish to upgrade the application to support differentiated pricing, which necessitates changing the data format as follows: rename the field price to fullPrice, and insert a new field named discountedPrice that is a markdown from the original price. The updated orderItems array (the last element of the JSON object) for the example, that adheres to the new format, is shown in Figure 1b.

To support migrating from the old to the new version of the application, Sadalage and Fowler suggest that the programmer can modify the new version’s code to essentially handle both formats, and migrate data from the old format to the new one when it is encountered.

This approach is efficacious but creates extra effort for the application programmer, as they have to write code that deals with the differing versions, and this code must reside in the application indefinitely. Sadalage and Fowler also do not explicitly consider the complications of concurrent clients, which could read/upgrade the data at the same time and produce inconsistencies. As we show later, handling this case...
C. DB upgrades using KVolve

KVolve’s architecture is depicted in Figure 2, with its two main elements depicted in green. In particular, the figure shows (at the top) an application installing an update specification in the database, signaling that the database’s contents need to be upgraded. And it shows two clients that are interacting with the database via KVolve’s client-side wrapper, which interposes on the basic NoSQL operations, i.e., gets and sets. KVolve’s wrapper is an extension of Redis-Py [18], the Python client suggested by the Redis website.

An update specification indicates the expected, current version identifier (in the figure, it’s v0); the new version identifier (here, v1); and code that can be used to migrate data from the current version to the new version (not shown). This code is written in our domain-specific language, illustrated in the next section and described in detail in Section III-A.

The wrapper used by clients provides roughly the same API as a standard Redis one, but performs three extra functions: It adds version information to keys mentioned in basic operations; it lazily migrates old data it encounters to the newest version; and it orchestrates a switchover to the newest application version when/if it falls behind the logical version of the data it is using.

The bottom of the figure shows a client interacting with the database after the update. Each get/set request is intercepted by the wrapper, which prepends the expected version (here, v1). Now, just after an update, there will be no keys at the newest version—all of the data is still at the last (or even older) versions. As such, the wrapper generates a query for earlier versions, typically by prepending an earlier version identifier (in the figure, v0). Generating old keys can be more complicated when keys change format; we discuss this situation in Section IV-B. If the wrapper finds older data it will update that data using the code provided in the update specification, and then store the updated version at the new-version key and delete the old data.

In the figure, we see the last function of the wrapper for the middle client. When the update is submitted, all existing clients are notified (using a standard Redis mechanism). The wrapper determines that the notification is due to the data version changing in a backward-incompatible manner. If we consider our purchase order example, we can see that the new version of the data will not work for older clients: They will be expecting JSON objects to contain field fullPrice, but the data will (eventually) be stored under fields discountedPrice and fullPrice, instead. As such, the old client cannot safely access the data any longer, and must be terminated.

When data is updated in a backward-incompatible manner, clients designed to use that data will have been re-coded to use the new format. As such, when the old version is notified, it can start a new-version replacement that connects to the database. That version then migrates the data as it accesses it, as described above. This approach simplifies application development as each application version can assume a particular data version, and the KVolve wrapper ensures data is migrated as it is needed. In fact, the only changes required to an application to support lazy data updates are to (a) change the call to connect to Redis to also declare the expected version of the data, and (b) to gracefully terminate when signaled to do so. These changes amount to only a few lines of code for the entire application.

D. Updating data using KVolve’s DSL

To make it easier for programmers to migrate data that has changed format, we developed a domain-specific language (DSL) for specifying the required changes. Our language supports changes to key names, as well as modifications to the contents of JSON objects; for the latter we support adding, deleting, renaming, and updating fields.
for order:: v0→v1 {
  INIT ["order", ["orderItems", "discountedPrice"]]
  $out = round($base['price'] * 0.7, 2)
  
  for f in e:
    assert(f is not None)
    if f['discountedPrice'] = round(f['price'] * 0.7, 2)
    if f['fullprice'] = f.pop('price')
  return (rediskey, jsonobj)
};

(a) DSL code specifying transformation

for group_0::update_order(rediskey, [jsonobj]):
  e = jsonobj.get('order').get('orderItems')
  assert(e is not None)
  for e in e:
    assert(f is not None)
    f['discountedPrice'] = round(f['price'] * 0.7, 2)
    f['fullprice'] = f.pop('price')
  return (rediskey, jsonobj)

(b) Generated Python code

Fig. 3: Specified update to purchase order objects

For the purchase order example, the data update is expressed in Figure 3a. The for statement indicates that all keys matching the regular expression order:: should be migrated from version v0 to version v1. KVolve does not presume any particular versioning scheme; strings like v0 and v1 are chosen by the developer. KVolve checks that the names correspond to a single chain of version updates, meaning that the developer cannot write an update for v0 to v1, and then later write an update for v0 to v2.

The body of this statement defines the changes to the values. First, the INIT on Line 2 indicates that a field with path order.orderItems.discountedPrice should be added to the JSON object. This path is defined using a list, where elements like orderItems in brackets indicate the JSON field is itself a list, so the update should be applied to each element of that list on the designated sub-path. The code on Line 3 initializes the new field to 0.7 times the value of the field price, rounded to two decimal places. This code is simply Python code with some DSL-specific variables contained in it, in this case $base and $out. The former is used to refer to the parent field of the one specified in the initialized list; here, therefore $base['price'] refers to the price field in the existing object that is a sibling of the newly added field. The $out special variable refers to the added field; here, we are therefore writing to the discountedPrice field.

Line 5 indicates that field price should be renamed to fullprice. Again, because orderItems is a list, this rename will be applied to all entries in the list.

DSL programs are compiled into normal Python code that is then stored with the update specification in the database, for later use by the KVolve wrappers. For our example, the generated code is given in Figure 3b. This function is called for each object whose key matches the specification; the updated object is returned (along with the potentially updated key, though in this case the key is unaffected).

for keyglob versold → versnew {
  DIRECTIVE path action-code
  ...
}

(a) Command to update JSON values

for namespace nsold → nsnew versold → versnew {
  optional-DIRECTIVES
}

(b) Command to update namespaces

Fig. 4: DSL commands

E. Namespace-based updates

So far we have suggested that updates are at the granularity of a whole application, but in fact, KVolve supports updates at a finer granularity. In particular, some data formats in a database may evolve (as will the applications that use them) while other data formats remain the same. Only those applications using affected data should be disrupted when an update takes place.

To achieve this goal, we can apply versioning not to the entire database, but rather to particular namespaces in the database. When an application connects to the database initially, it declares which namespaces it intends to access, and the expected versions. If the logical version of the data in the database (as determined by the most recently submitted update specification) matches the client’s declared version, the client may connect. Otherwise, the connection is refused, as a newer version of the client is required. Later, if a backward-incompatible update is submitted for a particular namespace, all clients that have declared they are using that namespace are notified, and they must reconnect at the newer version. Applications not using that namespace are not notified, and may proceed unfettered.

III. SPECIFYING UPDATES

This section explains how programmers can express database updates using KVolve’s domain specific language. We begin by defining the language’s syntax and semantics, and then present a series of examples. We also sketch how we compile DSL programs into Python code, using during lazy data migrations.

A. DSL syntax and semantics

An update specification consists of a sequence of DSL commands, which are processed in order. There are two basic kinds of commands. The first specifies changes to JSON values, and the second generalizes the first, also allowing changes to namespaces.

Updating values: The format of commands for updating values is given in Figure 4a. The keyglob is a simplified regular expression (allowing only ‘*’, ‘?’ and ‘[range]’) which identifies the keys of affected values. For example, the keyglob
order:may20+ might indicate only a range of purchase order invoice numbers are affected. The vers\_old and vers\_new strings identify the affected versions of the data.

The body of the for contains one or more commands, each beginning with a directive, which is the action to be performed. There are four possibilities, shown in Table I: initializing a new field, deleting a field, updating the value contained in a field, or renaming the field. The path is an index into the JSON object, such as ["order", ["orderItems"], "discountedPrice"] as shown on line 2 of Figure 3a. In the REN case the path part contains both a source and destination path.

The action-code of the command differs per directive, as shown in the third column of Table I. This code consists of a mix of special DSL tokens and Python code. The INIT and UPD directives are similar in that they both must specify the value that should be initialized or renamed. The DEL requires the code to return true or false, indicating whether a given path should, indeed, be deleted. Table II shows the DSL tokens that may appear in action code, which are interpreted specially by our DSL compiler. All of the directives’ action code may use any of the tokens, except INIT which may not use $in because an existing value does not exist for an initialized value.

Updating namespaces: The second command type generalizes the first, defining a change to the key namespace in addition to any changes to the values of the affected keys. This directive is particularly useful when the DSL writer wishes to change the prefix at the beginning of all of some set of keys. For example, a DSL writer may wish to rename namespace order: to be order:2015: for easier tracking. Any directives in the body of the for will apply to the values of any matched keys.

B. Example updates

Here we present two example updates: one to update JSON fields, the other to update namespaces.

1) Manipulating JSON fields: The purchase order example [13] in Section II-B showed how to add and rename JSON fields. Building on that example, suppose the next version (v2) expects the contents of field _id to be a decimal, rather than hexadecimal. On line 4 of Figure 5a, the DSL writer uses $in to access the field’s current value, and the action code converts it from hexadecimal, assigning the result to $out. Also suppose the next version avoids using the field since when it is later than orderdate. On line 7 of Figure 5a, the DSL writer uses the $base variable to access fields higher up in the JSON nesting structure than the field "since", determining whether the field should be deleted.

2) Renaming the database keys: Amico [19], a Redis-backed social network, added a scope suffix to certain namespaces between version 1.2 and 2.0. In version 1.2, namespaces were of the format amico:following and amico:reciprocated, whereas in version 2.0, they would have forms like amico:following:default v1.2→v2.0; amico:reciprocated:default v1.2→v2.0;

C. Implementing data transformations

The DSL code is translated into Python functions. In some cases multiple directives are combined into a single function, and in other cases there is one function per directive. These

<table>
<thead>
<tr>
<th>Directive</th>
<th>Path</th>
<th>Action code</th>
<th>Must Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>INIT</td>
<td>[json path, or empty for entire value]</td>
<td>Yes. (Assign value to $out)</td>
<td>None</td>
</tr>
<tr>
<td>UPD</td>
<td>[json path, or empty for entire value]</td>
<td>Yes. (Assign value to $out)</td>
<td>None</td>
</tr>
<tr>
<td>DEL</td>
<td>[json path, or empty for entire value]</td>
<td>Yes. (Code to determine what to delete.)</td>
<td>Bool</td>
</tr>
<tr>
<td>REN</td>
<td>[json path] → [json path]</td>
<td>No</td>
<td>None</td>
</tr>
</tbody>
</table>

TABLE I: The DSL Directives

<table>
<thead>
<tr>
<th>Token Meaning</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$out</td>
<td>the value of the path inside the [] in the Directive (this is the value to be updated, initialized, deleted, etc)</td>
</tr>
<tr>
<td>$in</td>
<td>the original value stored in the key (same as $out, but not written to)</td>
</tr>
<tr>
<td>$root</td>
<td>the root of the JSON structure,</td>
</tr>
<tr>
<td>$base</td>
<td>the same JSON structure, used to address siblings</td>
</tr>
<tr>
<td>$dbkey</td>
<td>the database key name currently being processed</td>
</tr>
</tbody>
</table>

TABLE II: The DSL Convenience Tokens
functions have the form shown in Figure 3b: they take the current key and value and return a potentially updated key and value. The body of each function is essentially the action code provided in the DSL specification with special variables (like $out) replaced by the appropriate accessor. For example, in Figure 3b the $base variable is replaced with Python variable e, and it is then used in the accessor for $out, which is the Python code f['discountedPrice']. Multiple directives in the same for block will apply to the same values, so sometimes we find it efficacious to generate a single function for multiple directives, e.g., when the paths are similar (as is the case in Figure 3b). Otherwise we will produce multiple functions but sequence their execution in the GET wrapper (Section IV-B) in the order in the given file. Our implementation borrows some code from JSON-delta [20].

The for namespace transformations potentially modify the Redis keys as well. This is largely straightforward, and we leave out further details for lack of space.

IV. IMPLEMENTING LAZY UPDATES

This section describes our implementation. We start by explaining how we install a dynamic update. Then we explain KVolve’s wrapper, which extends Redis-Py [18], the standard library-based client used by Python applications to access Redis. We focus on GET and SET operations, which are most prevalent, and then discuss other commands.

A. Installing an update

KVolve provides a special “update client” application for initiating an update. The developer invokes it by pointing it at the running Redis and passing the DSL file. Redis stores the current logical version of the data for each namespace ns under the special key __VERSION_NS. It also stores the compiled DSL (a Python module) and metadata for prior transformations, for each namespace. When the update client connects, it confirms that it is consistent with the existing versions, i.e., it is upgrading from the current logical version to the new one, for the affected namespaces. The update client uses a lightweight transaction to atomically update the logical versions of the namespaces, add the new DSL and metadata, and set a flag __UPDATE_IN_PROGRESS to true.

Next, it kills any clients that are now out of date with any logical namespace version. To do this, it uses the Redis command CLIENT LIST, which provides a list of all connected clients, then it uses the command CLIENT KILL to direct Redis to kill those clients that are potentially using out-of-date data. It identifies such clients by looking at the names of the clients in the list, which are set to include this version information when the clients connect. Once all clients have been killed, the __UPDATE_IN_PROGRESS flag is set to false.

At this point, it is safe for clients to connect. When they do, they will first check that they match the versions of data they are interested in, and then wait for the __UPDATE_IN_PROGRESS flag to be unset, if it is set. Clients that attempt to connect but are outdated will be refused, receiving a DeprecationWarning.

B. Get operations

As first mentioned in Section II-C, keys passed to both GET and SET operations are prepended with version information. In particular, each key k is rewritten to ver|k where ver is the expected version of data indexed by k. For example, the key key:123 might be rewritten to v1|key:123 if the current data version for namespace key is v1. Thus, when data is initially stored in the database using SET operations (discussed below), the data’s version is indicated by its key.

Basic approach: When the program calls GET k, the wrapper prepends the current version to k. If this call succeeds it immediately returns the (up-to-date) value. We expect this to be the common case.

If the lookup fails, there are two possible reasons: either (a) there simply is no data having the given key, at any version; or (b) there exists an earlier version of the data that must be migrated forward.

To see whether we are in the first case, the wrapper constructs all possible prior names of the key k; we generate all names because there could be very old data in the database (though only ever at one version). For now we ignore the fact that key names may evolve over time (due to for namespace commands), and therefore assume that older versions of the key simply differ in the prepended version. The list of names is ordered from newest to oldest, e.g., as ['v1|key:123', 'v0|key:123']. The wrapper then does a bulk-lookup of these keys using Redis’ MGET command, returning a list of corresponding values, with None for each key for which no value exists. If the list is all Nones then we are in case (a), and the wrapper can return None. If another client migrated the data in the meantime, the first element in the list (for the newest version) will be non-None, and so we can return that. Otherwise, we will see something like ['“None”, “... JSON value...”'], meaning there is a key at an earlier version, but not the current one; i.e., case (b).

To handle case (b), the wrapper begins a kind of lightweight transaction, called a pipe, and sets a watch on the new-version key. If the key is set or deleted by another thread during the transaction, it will abort. The wrapper then calls MGET again for the newest key and the non-None key previously discovered. Assuming that both are as they were prior to starting the transaction, the wrapper will generate a new version of the key and/or value using the relevant DSL transformation. (If the object is multiple versions behind, the transformations are composed oldest to newest.) Finally, the wrapper will store any new value (perhaps at a new key name), and delete the old value. Or, if only the key is renamed, it will simply rename the existing key. Then the transaction terminates. If successful, because the new key was not modified by another thread during the transaction, the updated value is returned; otherwise, the wrapper goes to the beginning and tries again, at which point it will find the key has been deleted or that the new version is available.

Making misses more efficient: The above algorithm works best when queries succeed; determining that a key is definitively not in the database requires two lookups: the one at
the newest version (which fails), and then the MGET at all versions. We could forego the first lookup in favor of always doing the second, but we find the second call is much more expensive, especially when there is a large number of possible previous versions.

As an optimization, when the wrapper discovers it is in case (a), it sets the queried key (at the current version) to have a sentinel value that indicates the key is morally absent. Then, the wrapper will identify this sentinel on subsequent GETs and return None. This approach trades space for time: storing the extra mapping ensures we have to perform only one lookup for each GET call, rather than two. Informal experiments found that this optimization could cut overhead by a third for workloads in which misses were more common.

Handling namespace changes: We simplified our description above by assuming that all versions of a key \( k \) are the same, aside from the prepended version identifier. But a key’s namespace can evolve according for namespace DSL commands (see Figure 4b). As such, the generated list of possible keys for the first MGET might need to be something like \(["v2\{newns:123\}", "v1\{ns:123\}", "v0\{ns:123\}\]\. To generate a list like this, we essentially run namespace transformations backwards. In particular, to transform the namespace from \( v1 \) to \( v2 \) in the above list, we would have had to have had a command:

```python
for namespace ns → newns v1 → v2:
```

The call GET newns:123 from the application would cause the wrapper to query the key \( v2\{newns:123\} \). When this fails, we run the above transformation backwards, to produce key \( v1\{ns:123\} \). The last key in the above list, \( v0\{ns:123\} \), would arise assuming that no namespace was transformed between versions \( v0 \) and \( v1 \).

C. Set operations

As with a GET, the wrapper for SET first prepends the version to the requested key. Then it performs the Redis call GETSET with the versioned-key, and the value. This call returns any prior version of the value mapped to be this key. If GETSET returns anything, then we know this data was previously migrated to the current version, so no additional versions of the data are present. On the other hand, if it returns nothing, then there are two cases: either (a) there was no data previously stored for this key, or (b) there was no data at the current version, but there could be at an older version. In case (a) we are done; in case (b) we need to delete the old data. To do this, we generate a list of all possible prior keys (following the same procedure as in the analogous case for GET) and delete all data associated with these keys.

SET can also be passed flags that modify its behavior. Flag NX instructs SET to only set \( k \) to \( v \) if \( k \) is not already in the database. Our wrapper must therefore check all versions \( k \) are absent before performing this command. Flag XX only performs the set when \( k \) is already present; it is handled similarly. Finally, flags EX and PX set an expiration timer for a key-value pair. Supporting this flag follows the basic logic for SET, but requires carrying forward the timeout during migration. The GET wrapper does this by querying the current time-to-live and setting it on the new value when it is migrated.

D. Other commands

Redis supports many more commands, but thus far our implementation has focused on GETs and SETs, as they are the core feature of applications that use Redis, in our experience.\(^2\) Supporting most other commands would be straightforward. For example EXIST checks the presence of a key—we wrapper would treat this similarly to GET. Or, APPEND appends to an existing mapped-to value; this would be handled similarly to SET XX.

Redis supports a variety of non-string-based data structures, including lists, SETs, and hashes. Newer versions of Redis have support for clustered data (i.e., coordinated Redis instances that each store different parts of a logical database). We plan to expand support for these features in future work.

V. EXPERIMENTAL RESULTS

This section considers the performance impact of KVoVe, both on normal operation, and during an update. Using variations of standard benchmarks, we find that KVoVe adds only 5–9% overhead during normal operation, and it significantly reduces the pause perceived by clients during an update, compared to a stop-the-world data migration. All experiments were performed on a computer with 24 processors (Intel(R) Xeon(R) CPU E5-2430 0 @ 2.20GHz) and 32 GB RAM, and run with PyPy 2.0.2 with GCC 4.4.7 on Red Hat 4.4.7-3. All tests report the median of 11 trials.

A. Steady State Overhead

An important question is how much extra overhead is imposed by the use of KVoVe’s wrapper during normal operation, i.e., while an update is not taking place. This overhead derives from the extra code in the wrapper that is used to lazily migrate data.

To measure this overhead we developed benchmarks based on the standard redis-benchmark, packaged with Redis, which measures the performance of various operations, including GETs and SETs. The benchmark uses 50 clients performing 20,000 requests each for a range of operations; for SETs and GETs the operations use a single key with a dummy value of size of 3 bytes (string "xx", which includes a NUL terminator). Redis-benchmark is written in C, and its use of a single key-value pair is not so meaningful in our setting, so we re-coded it in Python to use Redis-Py\(^{18}\) (and by extension, our wrapper) and to focus on GETs and SETs. We say more about the keys and values we use below.

Table III shows the steady state overhead for KVoVe compared using vanilla Redis-py. We show the results for benchmarks involving only GETs (columns 2 and 3) and only SETs (columns 4 and 5). We consider two cases: when all accesses are to keys already present in the database ("no

\(^{2}\) We also support DEL, which deletes keys (we try to delete the current version, and if no key exists, delete all versions, for good measure).
TABLE III: Comparing running time of KVolve and Redis (times in seconds)

<table>
<thead>
<tr>
<th></th>
<th>GET (only) miss</th>
<th>GET (only) 15% miss</th>
<th>SET (only) miss</th>
<th>SET (only) 15% miss</th>
</tr>
</thead>
<tbody>
<tr>
<td>KVolve</td>
<td>52.36s</td>
<td>53.83s</td>
<td>53.14s</td>
<td>54.04s</td>
</tr>
<tr>
<td>Redis-Py</td>
<td>49.89s</td>
<td>50.63s</td>
<td>50.03s</td>
<td>49.76s</td>
</tr>
<tr>
<td>Overhead %</td>
<td>4.95%</td>
<td>6.33%</td>
<td>6.21%</td>
<td>8.60%</td>
</tr>
<tr>
<td>Overhead (s)</td>
<td>2.47s</td>
<td>3.20s</td>
<td>3.11s</td>
<td>4.28s</td>
</tr>
</tbody>
</table>

Fig. 6: Lazy vs. Eager Updates for Gets and Sets Over the Full Range of 200,000 Keys

for the KVolve case (dashed line) dips briefly when an update thread requests an update, and all 50 clients disconnect and reconnect at the new version. Then the clients begin lazily updating the keys at a degraded rate as the keys are brought up to the current version. The old-version keys are shown in the finely-dashed line, and this number decreases at a constant rate as the keys are uniformly accessed lazily.

The Eager experiment (solid line) shows that all clients are stopped at 20 seconds at the beginning of the update. After about 40 seconds, the transformation is complete and the clients reconnect when they are signaled by the transformation thread at around 60 seconds on the timeline. Note that this pause time varies widely across runs. The pause time of 40 seconds shown in Figure 6 was the median of 11 trials, with a SIQR of 18.75 seconds. We think this variation in transforming the Redis database may be due to Python or PyPy, but we are still investigating the exact cause of variation of pause time.

Note that in this experiment, all clients access all keys in the entire database in a uniform pattern. This is the worst-case scenario for lazy updating, as opposed to the scenario where a smaller set of keys is constantly accessed and the rest of the database is rarely accessed. Lazy updates benefit the most from the later situation, whereas the Eager case suffers the most from that situation, having to transform old data that is rarely (or never) accessed.

Figure 7 shows the same experiment as above, except this time, the clients query only subset of 20,000 keys, representing a “hot” set of keys that get queried repeatedly. This setup allows KVolve to fully capitalize on lazy updates. Now, the KVolve case (dashed line) is able to very quickly return to full speed of execution and the clients experience minimal degradation, whereas the Eager case must still migrate the entire database, as less-frequently used keys might still need to be accessed.

These experiments show that data access patterns and number of database keys can alter the performance of KVolve and lazy updates. We plan to study how lazy updates and KVolve can bring the most benefit to a variety of applications in the future. In general, we demonstrated that in some cases KVolve
can greatly reduce pause time during updates with minimal performance penalty.

VI. RELATED WORK

In the realm of relational databases, the evolution of an application’s schema is characterized by the changes to the CREATE TABLE statements used to instantiate the schema in subsequent versions of the application. PRISM/PRISM++ [21] introduced a language of schema modification operators (SMOs) for expressing schema changes, based on the historical changes from the MediaWiki application that underlies Wikipedia. These SMOs capture most of the changes observed in the real world and enable generating the update code automatically and rewriting queries to adapt the application to the new version. However, complex schema changes often require taking the application offline or locking the database tables. For example, Wikipedia was locked for editing during the upgrade to MediaWiki 1.5, and the schema was converted to the new version in about 22 hours [22].

To address this problem, several professional tools have been created for performing ALTER TABLE operations in a non-blocking manner [23], [24], [25], [26], [27]. Because these tools focus only on the database, the changes implemented must be backward compatible to avoid breaking the application logic. To avoid this limitation, the Imago system [28] proposed installing the new version in a parallel universe, with dedicated application servers and databases, which allowed it to perform an end-to-end upgrade atomically. However, this approach duplicates resources and exposes the new version to the live workload only after the data migration was completed. In contrast, the F1 database from Google implemented an asynchronous protocol [29] for adding and removing tables, columns and indexes, which allows the servers in the database system to access and update all the data during a schema change and to transition to the new schema at different times. While F1 is implemented on top of a key-value store, the schema update model focuses on relational schema changes, rather than on changes to the low-level keys and values in the data store.

VII. CONCLUSIONS AND FUTURE WORK

This paper has presented KVolve, a general approach to evolving a NoSQL database without downtime. KVolve employs a wrapper that migrates data as it is accessed, reducing downtime that would otherwise result during a data upgrade, and minimizing required changes to applications. Data transformations specified by our domain specific language. We find that KVolve imposes minimal overhead when not performing an update (5–9% under intensive workloads).

In future work, we plan to consider an alternative implementation that does not link the wrapper with the client, but rather implements it as a language-independent proxy process. A lower-overhead alternative may be to implement it as a kind of plug-in to Redis itself. We also plan to add direct support for programmer-specified, backward-compatible updates, which would support continued operation without restarting clients. Finally, we expect to add support for other object formats aside from JSON, such as for Avro or Protocol Buffers.