Decibel: The Relational Dataset Branching System

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***Abstract*—As scientific endeavors and data analysis becomes increasingly collaborative, there is a need for data management systems that natively support the *versioning* or *branching* of datasets to enable concurrent analysis, cleaning, integration, manipulation, or curation of data across teams of individuals. Common practice for sharing and collaborating on datasets involves creating or storing multiple copies of the dataset, one for each stage of analysis, with no provenance information tracking the relationships between these datasets. This results not only in wasted storage, but also makes it challenging to track and integrate modifications made by different users to the same dataset. In this paper, we introduce the Relational Dataset Branching System, Decibel, a new relational storage system with built-in version control designed to address these shortcomings. We present our initial design for Decibel and provide a thorough evaluation of three versioned storage engine designs that focus on efficient query processing with minimal storage overhead. We also develop an exhaustive benchmark to enable the rigorous testing of these and future versioned storage engine designs.**

I. Introduction

With the rise of "data science", individuals increasingly find themselves working collaboratively to construct, curate, and manage shared datasets. Consider, for example, researchers in a social media company, such as Facebook or Twitter, working with a historical snapshot of the social graph. Different researchers may have different goals: one may be developing a textual analysis to annotate each user in the graph with ad keywords based on recent posts; another may be annotating edges in the graph with weights that estimate the strength of the relationship between pairs of users; a third may be cleaning the way that location names are attached to users because a particular version of the social media client inserted place names with improper capitalization. These operations may happen concurrently, and often analysts want to perform them on multiple snapshots of the database to measure the effectiveness of some an algorithm or analysis. Ultimately, the results of some operations may need to be visible to all users, while others need not be shared with other users or merged back into the main database.

Existing mechanisms to coordinate these kinds of operations on shared databases are often ad hoc. For example, several computational biology groups we interviewed at MIT to motivate our work reported that the way they manage such shared repositories is to simply make a new copy of a dataset for each new project or group member. Conversations with colleagues in large companies suggest that practices there are not much better. This ad hoc coordination leads to a number of problems, including:

- Redundant copies of data, which wastes storage.
- No easy way for users to share enhancements or patches to datasets with other users or merge them into the "canonical" version of the dataset.
- No systematic way to record which version of a dataset was used for an experiment. Often, ad hoc directory structures or loosely-followed filename conventions are used instead.
- No easy way to share data with others, or to keep track of who is using a particular dataset, besides using file system permissions.

One potential solution to this problem is to use an existing distributed version control system such as `git` or `mercurial`. These tools, however, are not well-suited to versioning large datasets for several reasons. First, they generally require each user to "checkout" a separate, complete copy of a dataset, which is impractical within large, multi-gigabyte or terabyte-scale databases. We envision instead a hosted solution, where users issue queries to a server to read or modify records in a particular version of the database. Second, because they are designed to store unstructured data (text and arbitrary binary objects), they have to use general-purpose differencing tools (like Unix diff) to encode deltas and compare versions. In contrast, deltas in databases can often be encoded as logical modifications to particular records or fields, which can be orders of magnitude smaller than the results of these general differencing tools, and are not sensitive to the order of the records. Moreover, version control systems like these do not provide any of the high-level data management features and APIs (e.g., SQL) typically found in database systems, relational or otherwise.

In this paper, we address the above limitations by presenting Decibel, a system for managing large collections of relational dataset versions. Decibel allows users to create working copies (i.e., *branches*) of a dataset based either off the present state of a dataset or from prior versions. As in existing version control systems such as `git`, many such branches or working copies can co-exist, and branches may be *merged* periodically by users. Decibel also allows modifications across different branches, or within the same branch.

We describe our versioning API and the logical data model we adopt for versioned datasets, and then describe several alternative approaches for physically encoding the branching structure. *Choosing the right physical data layout is critical for achieving good performance and storage efficiency from a versioned data store.* Consider a naive physical design that stores each version in its entirety: if versions substantially overlap (which they generally will), such a scheme will be hugely wasteful of space. Moreover, data duplication could

prove costly when performing cross-version operations like *diff* as it sacrifices the potential for shared computation.

In contrast, consider a *version-first* storage scheme which stores modifications made to each branch in a separate table fragment (which we physically store as a file) along with pointers to the table fragments comprising the branch's direct ancestors. A linear chain of such fragments thus comprises the state of a branch. Since modifications to a branch are co-located within single files, it is easier to read the contents of a single branch or version by traversing its lineage. However, this structure makes it difficult to perform queries that compare versions, e.g., that ask *which versions* satisfy a certain property or contain a particular tuple [1].

As an alternative, we also consider a *tuple-first* scheme where every tuple that has ever existed in any version is stored in a single table, along with a bitmap to indicate the versions each tuple exists in. This approach is very efficient for queries that compare the contents of versions (because such queries can be supported through bitmap intersections), but can be inefficient for queries that read a single version since data from many versions is interleaved.

Finally, we propose a *hybrid* scheme that stores records in segmented files like in the version-first scheme, but also leverages a collection of bitmaps like those in the tuple-first scheme to track the version membership of records. For the operations we consider, this system performs as well or better than both schemes above, and also affords a natural parallelism across most query types.

For each of these schemes, we describe the algorithms required to implement key versioning operations, including version scans, version differencing, and version merging. *The key contribution of this paper is a thorough exploration of the trade-offs between these storage schemes across a variety of operations and workloads.* Besides describing these schemes, this paper makes several other contributions:

- We provide the first full-fledged integration of modern version control ideas with relational databases. We describe our versioning API, our interpretation of versioning semantics within relational systems, and several implementations of a versioned relational storage engine.
- We describe a new versioning benchmark we have developed, modeled after several workloads we believe are representative of the use cases we envision. These workloads have different branching and merging structures, designed to stress different aspects of the storage managers.
- We provide an evaluation of our storage engines, showing that our proposed hybrid scheme outperforms the tuple-first and version-first schemes on our benchmark.

Decibel is a key component of DataHub [2], a collaborative data analytics platform that we're building. DataHub includes the version control features provided by Decibel along with other features such as access control, account management, and built-in data science functionalities such as visualization, data cleaning, and integration. Our vision paper on DataHub [2] briefly alluded to the idea of version and tuple-first storage, but did not describe any details, implementation, or evaluation, and also did not describe the hybrid approach presented here (which, as we show, outperforms the other approaches significantly, sometimes by an order-of-magnitude or more.) Also in recent work [3], we presented algorithms to minimize the storage and recreation costs of a collection of unstructured datasets, as opposed to building and evaluating an end-to-end structured dataset version management system like Decibel.

We begin by presenting motivating examples, showing how end users could benefit from Decibel. We then provide an overview of our versioning API and data model in Section II. A detailed overview of the aforementioned physical storage schemes is presented in Section III. We then describe our versioned benchmarking strategy in Section IV and the experimental evaluation of our storage models on a range of versioned query types in Section V.

A. Versioning Patterns & Examples

We now describe two typical dataset versioning patterns that we have observed across a wide variety of scenarios. We describe how they motivate the need for Decibel, and capture the variety of ways in which datasets are versioned and shared across individuals and teams. These patterns based on our discussions with domain experts, and inspire the workloads that we use to evaluate Decibel in Section V.

Science Pattern: This pattern is used by data scientist teams. These data scientists typically begin by taking the latest copy of an evolving dataset, then may perform normalization and cleaning (e.g., remove or merge columns, deal with NULL values or outliers), annotate the data with additional derived features, separate into test and training subsets, and run models as part of an iterative process. At the same time, the underlying dataset that the data scientists started with may typically evolve, but often analysts will prefer to limit themselves to the subset of data available when analysis began. Using Decibel, such scientists and teams can create a private branch in which their analysis can be run without having to make a complete copy of the data. They can return to this branch when running a subsequent analysis, or create further branches to test and compare different cleaning or normalization strategies, or different models or features, while retaining the ability to return to previous versions of their work.

This pattern applies to a variety of data science teams including *a*) The *ads team* of a startup, analyzing the impact of the ad campaigns on visitors to websites. *b*) A *physical scientist* team, who would like to build and test models and physical theories on snapshots of large-scale simulation data. *c*) A *medical data analysis* team, analyzing patient care and medical inefficiencies, who are only allowed to access records of patients who have explicitly agreed to such a study (this can be used to define branches that the team works on).

Curation Pattern: This pattern is used by teams collectively curating a structured dataset. While the canonical version of the dataset evolves in a linear chain, curators may work on editing, enhancing, or pruning portions of this dataset via branches, and then apply these fixes back to the canonical version. While this is cumbersome to do via current data management tools, Decibel can easily support multiple individuals simultaneously contributing changes to their branches, and then merging these changes back to the canonical version. This way, curators can "install and test" changes on branches without exposing partial changes to other curators or production teams using the canonical version until updates have been tested and validated.

This pattern applies to a variety of data curation teams including *a*) The team managing the *product catalog* of a business with individuals who manage different product segments, applying updates to their portion of the catalog in tandem. *b*) A volunteer team of community users contributing changes to a *collaboratively managed map*, e.g. OpenStreetMaps, where

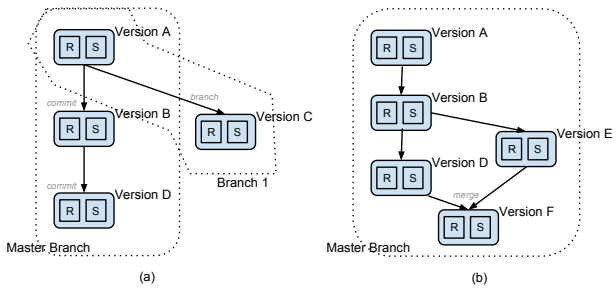


Fig. 1: An Example Workflow

#	*Query Type*	*SQL Equivalent*
1	*Single version scan*: find all tuples in relation R in version v01	`SELECT * FROM R WHERE R.Version = 'v01'`
2	*Multiple version positive diff*: positive diff relation R between versions v01 and v02	`SELECT * FROM R WHERE R.Version = 'v01' AND R.id NOT IN (SELECT id from R WHERE R.Version = 'v02')`
3	*Multiple version join*: join tuples in R in versions v01 and v02 satisfying Name = Sam	`SELECT * FROM R as R1, R as R2 WHERE R1.Version = 'v01' AND R2.Version = 'v02' AND R1.id = R2.id AND R1.Name = 'Sam'`
4	*Several version scan*: find all head versions of relation R	`SELECT * FROM R WHERE HEAD(R.Version) = true`

TABLE I: Sample Queries

individual users may focus on local regions, adding points of interest or fixing detailed geometry or metadata (e.g., one way information) of roads. *c*) A team of *botanists* collaboratively contributing to a dataset containing the canonical properties of plants found in a tropical rainforest.

II. Decibel API and Architecture

We begin with a brief overview of the Decibel architecture before describing the version control model and API that Decibel provides.

A. Architecture

We now briefly summarize the architecture of Decibel. Decibel is implemented in Java, on top of the MIT SimpleDB database. In this paper, we focus on the design of the Decibel storage engine, which is a new version-optimized data storage system able to implement the core operations to scan, filter, difference, and merge branching data sets. Note, however, that Decibel does support general SQL query plans, but most of our query evaluation (joins, aggregates) is done in the (unmodified) SimpleDB query planning layer. The changes we made for Decibel were localized to the storage layer. The storage layer reads in data from one of the storage schemes, storing pages in a fairly conventional buffer pool architecture with (with 4 MB pages), exposing iterators over different single versions of data sets. The buffer pool also encompasses a lock manager used for concurrency control. In addition to this buffer pool we store an additional version graph on disk and in memory. In this paper we focus on the versioned storage manager and versioning data structures, with support for versioning operations in several different storage schemes, not the design of the query executor. In the rest of this section, we describe Decibel query language.

B. Decibel Model and API

We first describe the logical data model that we use, and then describe the version control API in detail. We describe these concepts in the context of Figure 1, where (a) and (b) depict two evolution patterns of a dataset.

1) Data Model.: Decibel uses a very flexible logical data model, where the main unit of storage is the *dataset*. A dataset is a collection of *relations*, each of which consists of a collection of *records*. Each relation in each dataset must have a well-defined primary key; the primary key is used to track records across different versions or branches, and thus is expected to be immutable (a change to the primary key attribute, in effect, creates a new record). For the same reason, primary keys should not be reused across semantically distinct records; however, we note that Decibel does not attempt to enforce either of these two properties.

2) Version Control Model: Decibel uses a version control model that is similar to that of software version control systems like `git`. In Decibel, a *version* consists of a point-in-time snapshot of one or more relations that are semantically grouped together into a dataset (in some sense, it is equivalent to the notion of a `commit` in `git/svn`). For instance, Versions A—D in Figure 1(a) all denote versions of a dataset that contain two relations, R and S. A version, identified by an ID, is immutable and any update to a version conceptually results in a new version with a different version ID (as we discuss later in depth, the physical data structures are not necessarily immutable and we would typically not want to copy all the data over, but rather maintain differences). New versions can also be created by merging two or more versions (e.g., Version F in Figure 1(b)), or through the application of transformation programs to one or more existing versions (e.g., Version B from Version A in Figure 1(a)). The version-level provenance that captures these processes is maintained as a directed acyclic graph, called a *version graph*; the nodes and edges in Figure 1(a) or (b) comprise a version graph.

In Decibel, a *branch* denotes a working copy of a dataset. There is an active branch corresponding to every leaf node or version in the version graph. Logically, a branch is comprised of the history of versions that occur in the path from the branch leaf to the root of the version graph. For instance, in Figure 1(a) there are two branches, one corresponding to Version D and one corresponding to C. On the other hand, in Figure 1(b) there is a single branch corresponding to version F. The initial branch created is designated the *master* branch, which serves as the authoritative branch of record for the evolving dataset. Thus, a version can be seen as capturing a series of modifications to a branch, creating a point-in-time snapshot of a branch's content. The leaf version, i.e., the (chronologically) latest version in a branch is called its *head*; it is expected that most operations will occur on the heads of the branches.

3) Decibel Operational Semantics: We now describe the semantics of each of the core operations of the version control workflow described above as implemented in Decibel. Although the core operations Decibel supports are analogous to operations supported by systems like `git`, unlike those, Decibel supports in-place modifications to the data and needs to support both version control commands as well as data definition and manipulation commands. We will describe these operations in the context of Figure 1(a).

Users interact with Decibel by opening a connection to the Decibel server, which creates a *session*. A session captures the user's state, i.e., the commit (or the branch) that the operations the user issues will read or modify. Concurrent transactions by multiple users on the same version (but different sessions) are isolated from each other through two-phase locking.

Init: The repository is initialized, i.e., the first version (Version A in the figure) is created, using a special *init* transaction that creates the two tables as well as populates them with initial

data (if needed). At this point, there is only a single Master branch with a single version in it (which is also its head).

Commit and Checkout: *Commits* create new versions of datasets, adding an extra node to one of the existing branches in the version graph. Suppose a user increments the values of the second column by one for each record in relation R, then commits the change as Version B on the Master branch. This commit in Decibel creates a new logical snapshot of the table, and the second version in the master branch. Version B then becomes the new head of the Master branch. Any version (commit) on any branch may be *checked out*, modifying the user's current session state to point to that version. Different users may read versions concurrently without interference. For example, after making a commit corresponding to Version B, any other user could check out Version A and thereby revert the state of the dataset back to that state within their own session. Versions also serve as logical checkpoints for branching operations as described below.

In Decibel, every modification conceptually results in a new version. In update-heavy environments, this could result in a large number of versions, most of which are unlikely to be of interest to the users as logical snapshots. Hence, rather than creating a new version that the user can check out after every update (which would add overhead as Decibel needs to maintain some metadata for each version that can be checked out), we allow users to designate some of these versions as being interesting, by explicitly issuing commits. This is standard practice in source code version control systems like git and svn. Only such committed versions can be checked out. Updates made as a part of a commit are issued as a part of a single transaction, such that they become atomically visible at the time the commit is made, and are rolled back if the client crashes or disconnects before committing. Commits are not allowed to non-head versions of branches, but a new branch can be made from any commit. Concurrent commits to a branch are prevented via the use of two-phase locking.

Branch: A new branch can be created based off of any version within any existing branch in the version graph using the *branch* command. Consider the two versions A and B in Figure 1(a); a user can create a new branch, *Branch 1* (giving it a name of their choice) based off of Version A of the master branch. After the branch, suppose a new record is added to relation S and the change is committed as Version C on Branch 1. Version C is now the head of Branch 1, and Branch 1's lineage or ancestry consists of Version C and Version A. Modifications made to Branch 1 are not visible to any ancestor or sibling branches, but will be visible to any later descendant branches. The new branch therefore starts a new line of development starting from Version C.

Merge: At certain points, it may be desirable to *merge* two versions into a single branch, e.g., branches D and E into Branch F in Figure 1(b). Decibel supports any user specified *conflict resolution* policy to merge changes when the same record or records are changed across the branches that are being merged; by default, in our initial implementation, one branch is given precedence and is the authoritative version for each conflicting record.

The semantics of conflicts are different than those of a software version control system, where conflicts are at the text-line level within a file. Decibel tracks conflicts at the record level, though finer-granularity (i.e., field-level) conflict resolution is possible as well. Specifically, two records in Decibel are said to conflict if they (a) have the same primary key and (b) different field values. Additionally, a record that was deleted in one version and modified in the other will generate a conflict. Lastly, it is worth noting that in our merge approach, all parent branches and the new child branch are kept independent and isolated. In some version control models, the merge pulls changes into one of the parent branches.

Difference: Another important operation for Decibel is *diff*, useful for comparing two versions of a dataset. Given two versions A and B, diff will materialize two temporary tables: one representing the "positive difference" from A to B — the set of records in version B but not in A — and one representing the "negative difference", that is, the set of records in version B but not in A.

III. Physical Representations

In this section, we explore several alternative physical representations of our versioned data store. We begin by presenting two intuitive representations, the *tuple-first* and *version-first* models. The tuple-first model stores all records together, and uses an index to identify the branches a tuple is active in, whereas the version-first model stores all modifications made to each branch in a separate heap file, affording efficient examination of records in a single version. The tuple-first model outperforms on queries that compare across versions, while the version-first model underperforms for such queries; conversely, version-first outperforms for queries targeting a single version, while tuple-first underperforms. Finally, we present a *hybrid* storage model which bridges these approaches to offer the best of both. We now describe each of these implementations and how the core versioning functionality is implemented in each.

Note that we depend on a version graph recording the ancestor and branch relationships between the versions being available in memory in all approaches (this graph is updated and persisted on disk as a part of each branch or commit operation). As discussed earlier, we also assume that each record has a unique primary key.

A. Overview

Our first approach, called *tuple-first*, stores tuples from all branches in a single shared heap file. Although it might seem that the branch a tuple is active in could be encoded into a single value stored with the tuple, since tuples can be active in multiple branches, a single value insufficient. Instead, we employ a bitmap as our indexing structure to track which branch(es) each tuple belongs to. Bitmaps are space-efficient and can be quickly intersected for multi-branch operations.

There are two ways to implement tuple-first bitmaps. They can be *tuple-oriented* or *branch-oriented*. In a tuple-oriented bitmap, we store T bitmaps, one per tuple, where the ith bit of bitmap T_j indicates whether tuple j is active in branch i. Since we assume that the number of records in a branch will greatly outnumber the number of branches, all rows (one for each tuple) in a tuple-oriented bitmap are stored together in a single block of memory. In branch-oriented bitmaps, we store B bitmaps, one per branch, where the ith bit of bitmap B_j indicates whether tuple i is active in branch j. Unlike in the tuple-oriented bitmap, since we expect comparatively few branches, each branch's bitmap is stored separately in its own block of memory in order to avoid the issue of

Fig. 2: Example of Tuple-First

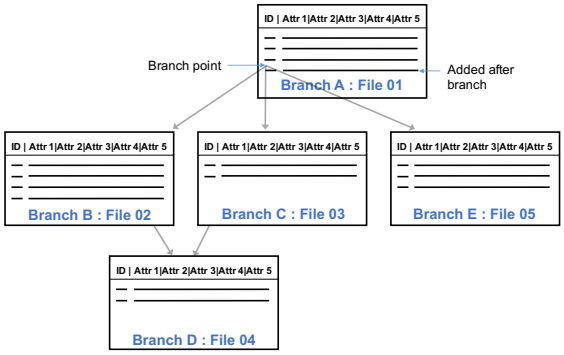


Fig. 3: Example of Version-First

needing to expand the entire bitmap when a single branch's bitmap overflows. Throughout this section, we describe any considerable implementation differences between these two approaches where appropriate.

Figure 2 shows the tuple-first approach with a set of tuples in a single heap file accompanied by a bitmap index indicating which tuples belong to one or more branches $A - E$. While tuple-first gives good performance for queries that scan multiple branches or that ask which branches some set of tuples are active in (for either tuple-oriented or branch-oriented variations), the performance of single branch scans can be poor as tuples in any branch may be fragmented across the heap file.

An alternative physical representation for encoding branches is the *version-first* approach. This approach stores modifications to each branch in a separate *segment file* for that branch. Each new child branch creates a new file with a pointer to the branch point in the ancestor's segment file; a collection of such segment files constitutes the full lineage for a branch. Any modifications to the new child branch are made in its own segment file. Modifications made to the ancestor branch will appear after the branch point in the ancestor's segment file to ensure this modification is not visible to any child branch. Ancestor files store tuples that may or may not be live in a child branch, depending on whether they been overwritten by a descendent branch. Figure 3 shows how each segment file stores tuples for its branch. This representation works well for single branch scans as data from a single branch is clustered within a lineage chain without interleaving data across multiple branches, but is inefficient when comparing several branches (e.g., performing a diff), as complete scans of branches must be performed (as opposed to tuple-first, which can perform such operations efficiently using bitmaps.)

The third representation we consider is a *hybrid* of version- and tuple-first that leverages the improved data locality of version-first while inheriting the multi-branch scan performance of tuple-first. In hybrid, data is stored in fragmented files as in version-first. Unlike version-first, however, hybrid applies a bitmap index onto the versioned structure as a whole by maintaining local bitmap indexes for each of the fragmented heap files as well as a single, global bitmap index which maps versions to the segment files which contain data live

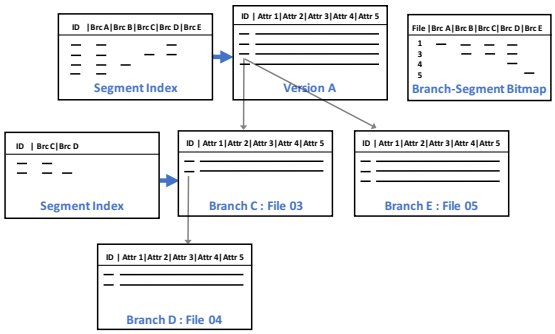


Fig. 4: Example of Hybrid

in that version. The local bitmap index of a segment tracks the versions whose bits are set for that segment in the global bitmap index, indicating the segment contains records live in that version. This is distinct from tuple-first which must encode membership for every branch and every tuple in a single bitmap index. Figure 4 shows how each segment has an associated bitmap index indicating the descendent branches for which a tuple is active. We omit the index for single version segments for clarity.

In the remainder of this section we discuss the how we implemented the core operations of branching, commits, scans, and diffs in each of these models. Our discussion focuses on how we minimized the number of repeated accesses to data in our implementation of these schemes.

B. Tuple-First Storage

Tuple-first stores tuples from different branches within a single shared heap file. Recall that this approach relies on a bitmap index with one bit per branch per tuple to annotate the branches a tuple is active in. As previously noted, this index could be either tuple (row) oriented or branch (column) oriented.

Branch: A branch operation clones the state of the parent branch's bitmap and adds it to the index as the initial state of the child branch. A simple memory copy of the parent branch's bitmap can be performed here. With a branch-oriented bitmap, this memory copy is straightforward; in the tuple-oriented case, however, the entire bitmap may need to be expanded (and copied) once a certain threshold of branches has been passed. This can be done with a simple growth doubling technique, increasing the amortized branching cost.

Commit: A commit on a branch in tuple-first stores a copy of the bits representing the state of that branch at commit time. Since we assume that operations on historical commits will be less frequent that those on the head of a branch, we keep historical commit data out of the bitmap index, instead storing this information in separate, compressed *commit history* files for each branch. This file is encoded using a combination of delta and run length encoding (RLE) compression. When a commit is made, the delta from the prior commit (computed by doing an XOR of the two bitmaps) is RLE compressed and written to the end of the file. To checkout a commit (version), we deserialize all commit deltas linearly up to the commit of interest, performing an XOR on each of them in sequence to recreate the commit. To speed retrieval, we aggregate runs of deltas together into a higher "layer" of composite deltas so that the total number of chained deltas is reduced, at the cost of some extra space. There could potentially be several of

such aggregate layers, but our implementation uses only two as commit checkout performance was found to be adequate (taking just a few hundred milliseconds).

Data Modification: When a new record is added to a branch, a set bit is added to the bitmap indicating the presence of the new record. When a record is updated in a branch, the index bit of the previous version of the record is unset in that branch's bitmap to show that the record is no longer active; as with inserts, we also set the index bit for the new, updated copy of the record inserted at the end of the heap file. Similarly, deletes are performed by updating the bitmap index to indicate that this record is not active in the branch. Because commits result in snapshots of bitmaps being taken, deleted and updated records will still be visible when reading historical commits; as such, old records cannot be removed entirely from the system. To support efficient updates and deletes, we store a primary-key index indicating the most recent version of each primary key in each branch.

The tuple-oriented case requires only that the new "row" in the bitmap for the inserted tuple be appended to the bitmap. However, we note that in a branch-oriented bitmap, the backing array of the bitmap may occasionally need to be expanded using a growth-doubling technique. Since each logical column of the bitmap is stored independently, overwriting the bounds of an existing branch's bitmap effectively requires only that logical column be expanded, not the bitmap as a whole.

Single-branch Scan: Often queries will only involve data for a single branch. To read all tuples in a branch in tuple-first, Decibel emits all records whose bit is set in that branch's bitmap. When the bitmap is branch-oriented, these bits are co-located in a single bitmap; in tuple-oriented bitmaps, the bits for a given branch are spread across the bitmaps for each tuple. As such, resolving which tuples are live in a branch is much faster with a branch-oriented bitmap than with a tuple-oriented bitmap because in the latter case the entire bitmap must be scanned.

Multi-branch Scan: Queries that operate on multiple branches (e.g., select records in branch A and B, or in A but not B) first perform some logical operation on the bitmap index to extract a result set of records relevant to the query. Tuple-first enables shared computation in this situation as a multi-branch query can quickly emit which branches contain any tuple without needing to resolve deltas; this is naturally most efficient with a tuple-oriented bitmap. For example, if a query is calculating an average of some value per branch, the query executor makes a single pass on the heap file, emitting each tuple annotated with the branches it is active in.

Diff: Recall that diff(A,B) emits two iterators, indicating the modified records in A and B, respectively. Diff is straightforward to compute in tuple-first: we simply XOR bitmaps together and emit records on the appropriate output iterator.

Merge: To merge two (or more) branches in tuple-first, records that are in conflict between the merged branches are identified. If a tuple is active in all of the merged branches, then the new child branch will inherit this tuple. The same is true if the tuple is inactive in all of the merged branches. Otherwise, if a tuple is active in at least one, but not all, of the parent branches, then we must check to see if this is a new record (in which case there is no conflict), whether it was updated in one branch but not the other (again, no conflict), or if it was modified in multiple branches (in which case there is a conflict).

To find conflicts, we create two hash tables, one for each branch being merged. These tables contain the keys of records that occur in one branch but not the other; we join them as we scan, performing a pipelined hash join to identify keys modified in both branches. Specifically, we perform a diff to find modified records in each branch. For each record, we check to see if its key exists in the other branch's table. If it does, the record with this key has been modified in both branches and is in conflict. If the record is not in the other branch's table, we add it to the hash table for its branch.

Conflicts can be sent to the user for resolution, or the user may specify that a given branch should take precedence (e.g., keep conflicts from A.) In this paper, we don't investigate conflict resolution policies in detail, and instead use precedence to resolve conflicts.

C. Version-First Storage

In version-first, each branch is represented by a head segment file storing local modifications to that branch along with a chain of parent head segment files from which it inherits records.

Branch: When a branch is created from an existing branch, we locate the current end of the parent segment file (via a byte offset) and create a *branch point*. A new child segment file is created that notes the parent file and the offset of this branch point. By recording offsets in this way, any tuples that appear in the parent segment after the branch point are isolated and not a part of the child branch. Any new tuples, or tuple modifications made in the child segment and are also isolated from the parent segment.

Commit: Version-first supports commits by mapping a commit ID to the byte offset of the latest record that is active in the committing branch's segment file. The mapping from commit IDs to offsets are stored in an external structure.

Data Modification: Tuple inserts and updates are appended to the end of the segment file for the updated branch. Updates are performed by inserting a new copy of the tuple with the same primary key and updated fields; branch scans will ignore the earlier copy of the tuple. Since there is no an explicit index structure to indicate branch containment for a record and since a branch cannot delete a record for historical reasons, deletes require a tombstone. Specifically, when a tuple is deleted, we insert a special record with a deleted header bit to indicate the key of the record that was deleted and when it was deleted.

Single-branch Scan: To perform branch scans, Decibel must report the records that are active in the branch being scanned, ignoring inserts, updates, and deletes in ancestor branches after the branch points in each ancestor. Note that the scanner cannot blindly emit records from ancestor segment files, as records that are modified in a child branch will result in two copies of the tuple: an old record from the ancestor segment (that is still active in the ancestor branch and any prior commit) and the updated record in the child segment. Therefore, the version-first scanner must be efficient in how it reads records as it traverses the ancestor files.

The presence of merges complicates how we perform a branch scan, so we first explain a scan with no merges in the version graph. In this case a branch has a simple linear ancestry of segment files back to the root of the segment tree. Thus, we can scan the segments in reverse order, ignoring records that

have already been seen, as those records have been overwritten or deleted by ancestor branch. Decibel uses an in-memory set to track emitted tuples. For example, in Figure 3 to scan branch D request that the segment for D be scanned first, followed by C, and lastly A up to the branch point. Each time we scan a record, that record is output (unless it is a delete) and added to the emitted tuple list (note that deleted records also need to be added to this emitted list). While this approach is simple, it does result in a higher memory usage to manage the in-memory set. Although memory usage is not prohibitive, were it to become an issue, it is possible to write these sets for each segment file to disk, and the use external sort and merge to compute record/segment-file pairs that should appear in the output. Merges require that the segments are scanned in a manner that resolves according to some conflict resolution policy, which is likely user driven. For example, on D the scan order could be $D-B-A-C$ or $D-B-C-A$.

Scanning a commit (rather than the head of a branch) works similarly, but instead of reading to the end of a segment file, the scanner starts at the commit point.

Decibel scans backwards to ensure more recently updated tuples will not be overwritten by a tuple with the same primary key from earlier in the ancestry. By doing so, we allow pipelining of this iterator as we know an emitted record will never be overwritten. However, reading segment files in reverse order leads to performance penalties as the OS cannot leverage sequential scans and pre-fetching. Our implementation seeks to lay out files in reverse order to offset this effect, but we omit details due to space reasons.

Merges result in a segment files with multiple parent files. As a result, a given segment file can appear in the multiple ancestor paths (e.g., if both parents branched off the same root). To ensure that we do not scan the same file multiple times, version-first must scan the version tree to determine the order in which segment files need to be read.

Multi-branch Scan: The single branch scanner is efficient in that it scans every heap file in the lineage of the branch being scanned only once. The multi-branch case is more complex because each branch may have an ancestry unique to the branch or it may share some common ancestry with other branches being scanned. The unique part will only ever be scanned once. For the common part, a naive version-first multi-branch scanner would simply run the single branch scanner once per branch, but this could involve scanning the common ancestry multiple times.

A simple scheme that works in the absence of merges is to topologically sort segment files in reverse order, such that segments are visited only when all of their children have been scanned. The system then scans segments in this order, maintaining the same data for each branch being scanned as in single-version scans. This ensures that tuples that were overwritten in any child branch will have been seen when the parent is scanned. Unfortunately, with merges the situation is not as simple, because two branches being scanned may need to traverse the same parents in different orders (e.g., a branch C with parents A and B where B takes precedence over A, and a branch D with parents A and B where A takes precedence over B). In this case, we do two passes over the segment files in the branches being considered. In the first pass, we build in-memory hash tables that contain primary keys and segment file/offset pairs for each record in any of the branches. Multiple hash tables are created, one for each portion of each segment file contained with any of the branches that is scanned. Each hash table is built by scanning the segment from the branch point backwards to the start of the segment file (so if two branches, A and B both are taken from a segment S, with A happening before B, there will be two such hash tables for S, one for the data from B's branch point to A's branch point, and one from A to the start of the file.) Then, for each branch, these in-memory tables can be scanned from leaf-to-root to determine the records that need to be output on each branch, just as in the single-branch scan. These output records are added to an output priority queue (sorted in record-id order), where each key has a bitmap indicating the branches it belongs to. Finally, the second pass over the segment files emits these records on the appropriate branch iterators.

Diff: Diff in version-first is straightforward, as the records that are different are exactly those that appear in the segment files after the earliest common ancestor version. Suppose two branches B_1 and B_2 branched from some commit C in segment file F_C; creating two segment files F_1 and F_2. Their difference is all of the records that appear F_1 and F_2. If B_1 branched from some commit C_1 and B_2 branched from a later commit C_2, then the difference is the contents of F_1 and F_2, plus the records in F_C between C_1 and C_2.

Merge: Merging involves creating a single child branch with two (or more) branch points, with one for each parent. In a simple precedence based model, where all the conflicting records from exactly one parent are taken and the conflicting records from the other parent are discarded, all that is required is to record the priority of parent branches so that future scans can visit the branches in appropriate order, with no explicit scan required to identify conflicts.

To allow the user to manually resolve conflicts, we need to identify records modified in both branches. The approach uses the general multi-branch scanner to scan the segment files of the two branches as far back as their earliest common ancestor. We materialize the primary keys of the records in one branch into an in-memory hash table, inserting every key. Deleted records are also output. We then scan the other branch; if a key appears in both branches, it must have been modified by both and is thus a conflict (note that we could compare the contents to see if they are identical but this would require an additional read). Merge can stop at the lowest common ancestor, as any record appearing here or earlier will be present in both branches.

D. Hybrid Storage

Hybrid combines the two storage models presented above to obtain the benefits of both. It operates by managing a collection of *segments*, each consisting of a single heap file (as in version-first) accompanied by a bitmap-based *segment index* (as in tuple-first). As described in Section III-A, hybrid uses a collection of smaller bitmaps, one local to each segment. Each local bitmap index tracks only the set of branches which inherit records contained in that segment; this contrasts with the tuple-first model which stores liveness information for all records and all branches within a single bitmap. Additionally, a single *branch-segment bitmap*, external to all segments, relates a branch to the segments that contain at least one line record in the branch. Bit-wise operations on this bitmap yield the set of segments containing records in any logical aggregate of branches. For example, to find the records represented in either

of two branches, one need only consult the segments identified by the logical OR of the rows for those branches within this bitmap. This enables a scanner to skip segments with no active records and allows for parallelization of segment scans.

As in the version-first scheme, this structure naturally co-locates records with common ancestry, but with the advantage that the bitmaps make it possible to efficiently perform operations across multiple branches (such as differences and unions) efficiently, as in the tuple-first scheme.

In hybrid, there are two classes of segments: *head segments* and *internal segments*. Head segments track the evolution of the "working copy" of a single branch; fresh modifications to a branch are placed into that branch's head segment. Head segments become internal segments after a commit or branch operation, at which point the contents of the segment are frozen, such that only the segment's bitmap may change.

We now describe the details of how specific operations are performed in hybrid.

Branch: Branch creates two new head segments that point to the prior parent head segment: one for the parent and one for the new child branch. The old head of the parent becomes an internal segment with records in both branches (note that its bitmap is expanded). These two new head segments are added as columns to the branch-segment bitmap, initially marked as present for only a single branch, while a new row is created for the new child branch (creation of the new head segments could, in principle, be delayed until a record is inserted or modified.) As in tuple-first, the creation of a new branch requires that all records live in the direct ancestor branch be marked as live in a new bitmap column for the branch being created. Unlike the tuple-first model, however, a branch in hybrid instead requires a bitmap scan be performed only for those records in the direct ancestry instead of on the entire bitmap.

Commit: The hybrid commit process is analogous to that of the tuple-first model except that the bitmap column of the target branch of the commit must be snapshotted within each segment containing records in that branch, as well as the branch's entry in the branch-segment bitmap.

Data Modification: The basic process for inserts, deletes, and updates is as in tuple-first. Updates require that a new copy of the tuple is added to the branch's head segment, and that the segment with the previous copy of the record have the corresponding segment index entry updated to reflect that the tuple in prior segment is no longer active in this branch. If the prior record was the last active record in the segment for the branch being modified, then the branch-segment bitmap is updated so that the segment will not be considered in future queries on that branch.

Single-branch Scan: Single branch scans check the branch-segment index to identify the segments that need to read for a branch. Thus, as in tuple-first, a segment read filters tuples based on the segment index to only include tuples that are active in the branch. Due to the branch-segment index, the segments do not need to be scanned in a particular order.

Multi-branch Scan: As in tuple-first, multi-branch scans require less work than in version-first as we can pass over each tuple once, using the segment-index to determine how to apply the tuple for scan. However, compared with tuple-first, hybrid benefits from scanning fewer records as only the segments that correspond to the scanned branches need to be read.

Diff: The differencing operation is again performed similarly to the tuple-first model except that only the set of segments containing records in the branches being differenced are consulted. The storage manager first determines which segments contain live records in either branch, then each segment is queried to return record offsets comprising the positive and negative difference between those branches within that segment. The overall result is an iterator over the union of the result sets across all pertinent segments.

Merge: Merging is again similar to the tuple-first model except that the operation is localized to a particular set of segments containing records in the branches involved in the merge operation. As in tuple-first, a conflict is output for records which have been modified in at least one of the branches being merged. The original copies of these records in the common ancestry are then scanned to obtain their primary keys and thus the record identifiers of the updated copies within each branch being merged. Subsequently, any join operation may be used once the identifiers of conflicting records have been obtained. Once conflicts have been resolved, the records added into the child of the merge operation are marked as live in the child's bitmaps within its containing segments, creating new bitmaps for the child within a segment if necessary.

E. Discussion

The previous sections discussed the details of the three schemes. We now briefly summarize the expected differences between their performance to frame the evaluation. Tuple-first's use of bitmaps allows it to be more efficient at multi-branch scans, but its single heap file does poorly when records from many versions are interleaved. Bitmap management can also be expensive. Version-first, in contrast, co-locates tuples from a single version/branch, so does well on single-branch scans, but because it lacks an index performs poorly on multi-version operations like diff and multi-version scan. Hybrid essentially adds a bitmap to version-first to allow it to get the best of both worlds.

IV. Versioning Benchmark

To evaluate Decibel, we developed a new versioning benchmark to measure the performance of our versioned storage systems on the key operations described above. The benchmark consists of four types of queries run on a synthetically-generated versioned dataset, generated using one of four branching strategies, described next.

The benchmark is designed as a single-threaded client that loads and updates data according to branching strategy, and measures query latency. Although highly concurrent use of versioned systems is possible, we believe that in most cases these systems will be used by collaborative data analytics and curation teams where high levels of concurrency in a single branch is not the norm.

A. Branching Strategies

Branches in these datasets are generated according to one of four branching strategies. The first two patterns, deep and flat, are not meant to be representative of real workloads, but instead serve as extremes that stress different aspects of the storage engines. The remaining two patterns are modeled on typical branching strategies encountered in practice and also described in Section I-A. Figure 5 shows these strategies.

Deep: This is a single, linear branch chain. Each branch is created from the end of the previous branch, and each branch

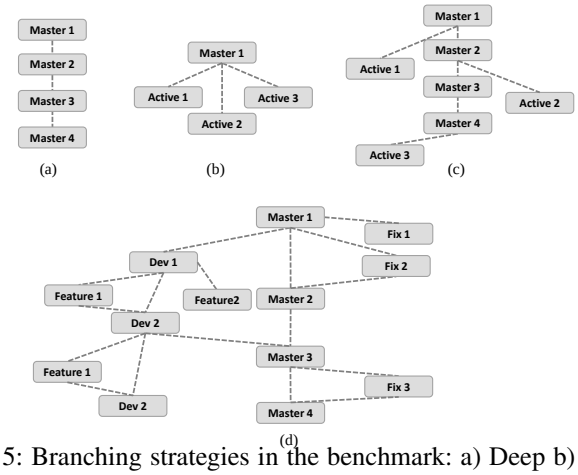


Fig. 5: Branching strategies in the benchmark: a) Deep b) Flat c) Science (Sci.) d) Curation (Cur.).

has the same number of records. Here, once a branch is created, no further records are inserted to the parent branch. Thus, inserts and updates always occur in the branch that was created last. Single-version scans are performed on the tail, while multi-branch operations select the tail in addition to its parent or the head of the structure.

Flat: Flat is the opposite of deep. It creates many child branches from a single initial parent. Again, each branch has the same number of records. For single-version scans, we always select the newest branch, though this choice is arbitrary as all children are equivalent. For multi-branch operations, we use the single common ancestor branch plus one or more randomly-selected children.

Science: As in the data science pattern in Section I-A, each new branch either starts from some commit of the master branch ("mainline"), or from the head of some existing active working branch. This is meant to model a canonical (evolving) data set that different teams work off of. There are no merges. Each branch lives for a fixed lifetime, after which it stops being updated and is no longer considered active. All single-branch modifications go to either the end of an active branch or the end of mainline. Inserts may be optionally skewed in favor of mainline. Unless specified otherwise, single and multi-version scans select either the mainline, oldest active branch, or youngest active branch with equal probability.

Curation: As in the data curation pattern described in Section II, there is one master data set (e.g., the current road network in OpenStreetMaps), that is on a mainline branch. Periodically "development" branches are created from the mainline branch. These development branches persist for a number of operations before being merged back into the mainline branch. Moreover, short-lived "feature" or "fix" branches may be created off the mainline or a development branch, eventually being merged back into its parent. Data modifications will occur randomly across the heads of the mainline branch or any of the active development, fix, or feature branches (if they exist). Unless specified otherwise, single or multi-version scans will randomly select among the mainline branch and the active development, fix, and feature branches (if they exist).

B. Data Generation and Loading

In our evaluation, generated data is first loaded and then queried. The datasets we generate consist of a configurable number of randomly generated 4-byte integer columns, with a single integer primary key. We fix the record size (1KB), number of columns (250), page size (4 MB), and create commits at regular intervals (every 10,000 insert/update operations per branch). The benchmark uses a fixed mix of updates to existing records and inserts of new records in each branch (20% updates and 80% inserts by default in our experiments).

For each branching strategy described earlier, we vary the dataset size, the number of branches, and the branches targeted in each query. The benchmark also supports two loading modes, *clustered* and *interleaved*. In clustered mode, inserts into a particular branch are batched together before being flushed to disk. In our evaluation, we only consider the interleaved mode as we believe it more accurately represents the case of users making concurrent modifications to different branches. In interleaved mode, each insert is performed to a randomly selected branch in line with the selected branching strategy: for deep, only the tail branch accepts inserts; for flat, all child branches are selected uniformly at random; for the data science and data curation strategies, any active branch is selected uniformly at random (recall that those strategies may "retire" branches after a certain point). The benchmark additionally supports insert skew for non-uniform insertion patterns; our evaluation of the scientific strategy favors the mainline branch with a 2-to-1 skew, for example.

C. Evaluated Queries

The queries targeted in our benchmark are similar to those in Table I; we summarize them briefly here.

Query 1: Scan and emit the active records in a single branch.
Query 2: Compute the difference between two branches, $B1$ and $B2$. Emit the records in $B1$ that do not appear in $B2$.
Query 3: Scan and emit the active records in a primary-key join of two branches, $B1$ and $B2$, that satisfy some predicate.
Query 4: A full dataset scan that emits all records in the head of any branch that satisfy a predicate. The output is a list of records annotated with their active branches.

Our benchmarking software, including a data generator and benchmark driver (based on YCSB [4]), is available at http://datahub.csail.mit.edu/www/decibel.

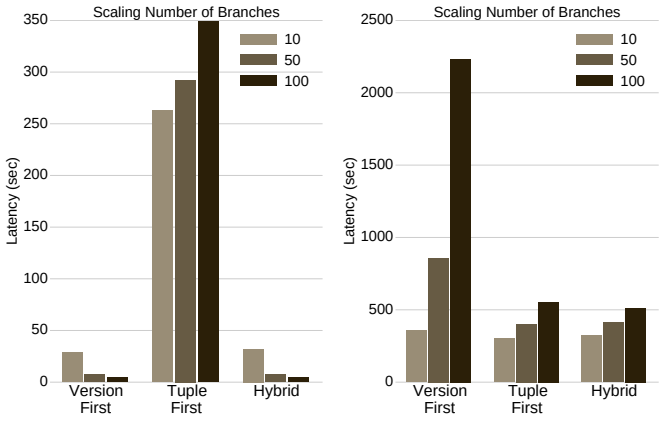
V. Evaluation

In this section, we present our evaluation of Decibel on the versioning benchmark. The goals of our evaluation are to compare the relative performance of the version-first, tuple-first, and hybrid storage schemes for the operations described in Section IV. We first examine how each of the models scales with the number of branches introduced to the system. Next, we examine relative performance across the query types described in Section IV-C for a fixed number of branches. We then examine the performance of each model's commit and snapshot operations. Finally, we conclude by comparing loading times for each storage model.

We note that for the tuple-first and hybrid models, we focus our evaluation on a branch-oriented bitmap due to its suitability for our commit procedure. Additionally, we note that disk caches were flushed prior to each operation to eliminate the effects of OS page caching.

A. Scaling Branches

Here we examine how each storage model scales with the number of branches introduced into the version graph. We focus on deep and flat branching strategies as these patterns



(a) Query 1 on Flat (b) Query 4 on Deep

Fig. 6: The Impact of Scaling Branches

represent logical extremes to designed to highlight differences between the three designs. Moreover, we examine only Query 1 (scan one branch) and Query 4 (scan all branches) as these queries also represent two fundamental extremes of versioning operations.

Figure 6a shows how the storage models scale across structures with 10, 50, and 100 branches for Query 1 on the flat branching strategy. As tuple-first stores records from all versions into a single heap file, ordered by time of insertion, we see single-branch scan times for tuple-first greatly underperform both version-first and hybrid. Note that the latencies for version-first and hybrid decline here since the total data set size is fixed at 100GB, so each branch in the flat strategy contains less data as the number of branches is increased. On the other hand, tuple-first's performance deteriorates as the bitmap index gets larger. In contrast, Query 1 on the deep structure (not shown for space reasons) results in uniform latencies as expected (250 seconds $\pm 10\%$) for each storage model and across 10, 50, and 100 branches as all branches must be scanned.

Unlike Query 1, Query 4 (which finds all records that satisfy a non-selective predicate across versions) shows where version-first performs poorly. The results are shown in Figure 6b. This figure shows the performance issue inherent to the version-first model for Query 4. Performing this query in version-first requires a full scan of the entire structure to resolve all differences across every branch. The tuple-first and hybrid schemes, on the other hand, are able to use their bitmap indexes to efficiently answer this query.

The intuition in Section III is validated for the version- and tuple-first models: the tuple-first scheme performs poorly in situations with many sibling branches which are updated concurrently, while the version-first model performs poorly on deep multi-version scans. Additionally, in both cases hybrid is comparable with the best scheme, and exhibits good scalability with the number of branches.

B. Query Results

Next, we evaluate all three storage schemes on the queries and branching strategies described in Section IV. All experiments are with 50 branches. Note that the deep and flat strategies were loaded with a fixed 100 GB dataset, but the scientific and curation strategies were loaded with a fixed number of branches to result in a dataset as close to 100 GB as possible, but achieving this exactly was not possible.

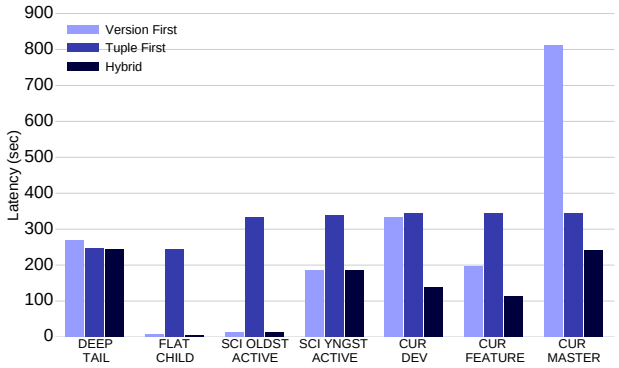


Fig. 7: Query 1

Query 1 (Q1): Figure 7 depicts the results of Query 1 across each storage model. Here, we scan a single branch and vary the branching strategy and active branch scanned. The bars are labelled with the branching strategy and the branch being scanned. For deep, we scan the latest active branch, the tail. Since each successive branch is derived from all previous branches, this requires all data to be scanned. Note that we are scanning 100 GB of data in about 250s, for a throughput of around 400 MB/sec; this is close to raw disk throughput that we measured to be 470 MB/sec using a standard disk diagnostic tool (hdparm). For flat, we select a random child. For tuple-first this results in many unnecessary records being scanned as data is interleaved. The use of large pages increases this penalty, as an entire page is fetched for potentially a few valid records. Something similar happens in scientific (sci). Both the youngest and oldest active branch and branches have interleaved data that results in decreased performance for tuple-first. When reading a young active branch, more data is included from many mainline branches, which results in a higher latency for version-first and hybrid in comparison to reading the oldest active branch. Tuplefirst has to read all data in both cases. For curation (cur.), we read either a random active development branch, a random feature branch, or the most recent mainline branch. Here, tuple-first exhibits similar performance across use cases, as it has to scan the whole data set. Version-first and hybrid exhibit increasing latencies largely due to increasingly complicated scans in the presence of merges. As the level of merges for a particular branch increases (random feature to current feature to mainline), so does the latency. As expected version-first has increasingly worse performance due to its need to identify the active records that are overwritten by a complicated lineage, whereas hybrid leverages the segment-indexes to identify active records while also leveraging clustered storage to avoid reading too many unnecessary records. Thus, in this case, hybrid outperforms both version and tuple-first.

Query 2 (Q2): Figure 8 shows the results for Q2. Recall that Q2 does a diff between two branches. In the figure we show four cases, one for each branching strategy: 1) diffing a deep tail and it's parent; 2) diffing a flat child and parent; 3) diffing the oldest science active branch and the mainline; and 4) diffing curation mainline with active development branch. Here, version-first uniformly has the worse performance due to the complexity and need to make multiple passes over the dataset to identify the active records in both versions. This is in part due to the implementation of diff in version-first not incrementally tracking differences between versions from a common ancestor. Tuple-first and hybrid are able to leverage

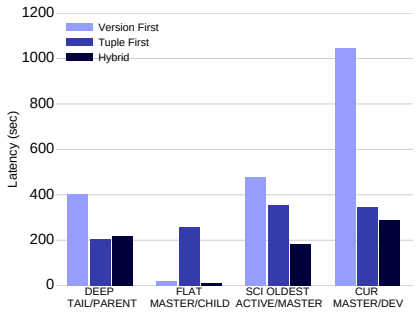


Fig. 8: Query 2

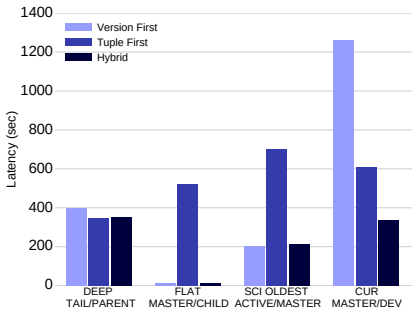


Fig. 9: Query 3

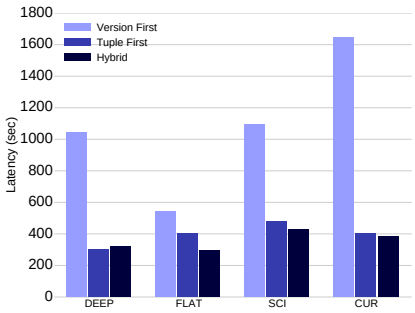


Fig. 10: Query 4

		Agg. Pack File Size (MB)	Avg. Commit Time (ms)	Avg. Checkout Time (ms)
DEEP	TF	234	15	501
	HY	198	13	25
FLAT	TF	532	86	193
	HY	155	10	66
SCI	TF	601	35	544
	HY	277	9	836
CUR	TF	510	10	570
	HY	280	6	43

TABLE II: Bitmap Commit Data (50 Branches)

the index to quickly identify the records that are different between versions. As the amount of interleaving increases (dev to flat), we see that hybrid is able to scan and compare fewer records than tuple-first, resulting in lower query latency.

Query 3 (Q3): Figure 9 depicts the results for Q3 which scans two versions, but finds the common records that satisfy some predicate. This is effectively a join between two versions. The trends between Q2 and Q3 are similar, however for version-first in Q2 we must effectively scan both versions in their entirety as we cannot rely on metadata regarding precedence in merges to identify the differences between versions. In Q3, we perform a hash join for version-first and report the intersection incrementally; in the absence of merges, the latencies are better (comparable with hybrid), but in curation with a complex ancestry we need two passes to compute the records in each branch and then another pass to actually join them.

Query 4 (Q4): Figure 10 depicts the results for Q4 with full data scans to emit the active records for each branch that match some predicate. We use a very non-selective predicate such that sequential scans are the preferred approach. As expected tuple-first and hybrid offer the best (and comparable) performance due to their ability to scan each record once to determine if which branch's the tuple should be emitted to. Version-first however, must sometimes make multiple passes to identify and emit the records that are active for each branch; in particular this is true in the curation workload, where there are merges. In addition, version-first has a higher overhead for tracking active records (as a result of its need to actively materialize hash tables containing satisfying records). The deeper and more complicated the branching structure, the worse the performance for version-first is. Also note in flat, hybrid outperforms tuple-first with near max throughput. This largely due to working with smaller segment indexes instead of a massive bitmap.

C. Bitmap Commit Performance

We now evaluate the commit performance of the different strategies. Our benchmark performed commits at fixed intervals of 10,000 updates per branch. Table II reports the aggregate on-disk size of the compressed bitmaps for the tuple-first and hybrid schemes as well as averages of commit creation and checkout times. The aggregate size reported includes the full commit histories for all branches in the system. Recall from Section III-B that in tuple-first the commit history for each branch is stored within its own file; in hybrid, each (branch, segment) has its own file. This results in a larger number of smaller commit history files in the hybrid scheme.

Commit time and checkout time was evaluated by averaging the time create/checkout a random set of 1000 commits agnostic to any branch or location. Checkout times for hybrid are better since the total logical bitmap size is smaller (as bitmaps are split up) and the fragmentation of inserts in tuple-first increases dispersion of bits in bitmaps, enabling less compression. Note that the overall storage overheads are less than 1% of the total storage cost in all cases, and commit and checkout times are less than 1 second in all cases. We flushed disk caches prior to each commit/checkout in this experiment.

VI. Related Work

Temporal databases have long been a subject of academic research [5], [6], [7], [8], [9]. The "time-travel" features of such systems provide the ability to query point-in-time temporal snapshots of a database which essentially comprise a linear chain of historical branches. Since a branched system lacks a total ordering of branches, temporal methods explored in this body of work do not apply to Decibel. There is also prior work on temporal RDF data and temporal XML Data. Motik [10] presents a logic-based approach to representing valid time in RDF and OWL. Several papers (e.g., [11], [12]) have considered the problems of subgraph pattern matching or SPARQL query evaluation over temporally annotated RDF data. There is also much work on version management in XML data stores and scientific datasets [13], [14], [15]. These approaches are largely specific to XML or RDF data, and cannot be directly used for relational data; for example, many of these papers assume unique node identifiers to merge deltas or snapshots.

The general concept of multi-versioning has also been used extensively in commercial databases to provide snapshot isolation [16], [17]. However, these methods only store enough history to preserve transactional semantics, whereas Decibel preserves historical records to ensure the integrity of a branched lineage.

Some operations in Decibel include provenance tracking at the record or version level. Provenance tracking in databases and scientific workflow systems has been studied extensively as well (see, e.g., [18], [19], [20], [21], [22]). But those systems do not include any form of collaborative version control, and

do not support unified querying and analysis over provenance and versioning information [1].

Existing software version control systems like git and mercurial inspired this work [23], [24]. As mentioned above, while these systems work well for modest collections of relatively small text or binary files, they are not well-suited for large sets of structured or semi-structured data. Moreover, they do not provide features of mature data management systems such as transactional guarantees or high-level query and analytics interfaces. Instead, Decibel ports the broad API and workflow model of these systems to a traditional relational database management system.

There exists a considerable body of work on "fully-persistent" data structures, B+Trees in particular [25], [26], [27]. Some of this work considers branched branches, but is largely focused on B+Tree-style indexes that point into underlying data consisting of individual records, rather than accessing the entirety or majority of large datasets from disk. Jiang et al. [28] present the *BT-Tree* which is designed as an access method for "branched and temporal" data. Each update to a record at a particular timestamp constitutes a new "version" within a branch. Unfortunately, their versioning model is limited and only supports trees of versions with no merges; furthermore, they do not consider or develop algorithms for the common setting of scanning or differencing multiple versions.

A recent distributed main-memory B-Tree [29] considers branchable clones which leverage existing copy-on-write algorithms for creating cloneable B-Trees [25]. However, like the BT-Tree, these methods heavily trade off space for point query efficiency and therefore make snapshot creation and updating very heavyweight operations. Nonetheless, the authors do not profile any operations upon snapshots but only the snapshot creation process itself. Merging and differencing of data sets are again not considered.

Even discounting the inherent differences between key-value and relational storage models, none of the aforementioned work on multi-versioned B-Trees considers the full range of version control operations and ad hoc analytics queries that we consider with Decibel. In general, B-Trees are appropriate for looking up individual records in particular versions, but are unlikely to be useful in performing common versioning operations like scan, merge, and difference, which are our focus in this paper.

Finally, we note that we have published related work on data set versioning and differencing within the contexts of graph systems [30] and scientific array database [31]. Decibel represents an effort to expand the spirit of that work to a broader class of structured data sets and analytics queries.

VII. Conclusion

We presented Decibel, our database storage engine for managing and querying large numbers of relational dataset versions. To the best of our knowledge, Decibel is the first implemented and evaluated database storage engine that supports arbitrary (i.e., non-linear) versioning of data. We evaluated three physical representations for Decibel, and compared and contrasted the relative benefits of each, and identified hybrid as the representation that meets or exceeds the performance of the other two representations; we also evaluated column and row-oriented layouts for the bitmap index associated with each of these representations. In the process, we also developed a versioning benchmark to allow us to compare these representations as well as representations developed in future work.

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