Version Reconciliation for Collaborative Databases

Nalin Ranjan  
Princeton University  
nranjan@princeton.edu

Zechao Shang∗  
zechao.shang@snowflake.com  
Snowflake Inc.

Aaron J. Elmore  
Sanjay Krishnan  
aelmore@cs.uchicago.edu  
skr@uchicago.edu  
University of Chicago

ABSTRACT
We propose MindPalace, a prototype of a versioned database for efficient collaborative data management. MindPalace supports offline collaboration, where users work independently without real-time correspondence. The core of MindPalace is a critical step of offline collaboration: reconciling divergent branches made by simultaneous data manipulation. We formalize the concept of auto-mergeability, a condition under which branches may be reconciled without human intervention, and propose an efficient framework for determining whether two branches are auto-mergeable and identifying particular records for manual reconciliation.

ACM Reference Format:
Nalin Ranjan, Zechao Shang, Aaron J. Elmore, and Sanjay Krishnan. 2021. Version Reconciliation for Collaborative Databases. In ACM Symposium on Cloud Computing (SoCC ’21), November 1–4, 2021, Seattle, WA, USA. ACM, New York, NY, USA, 18 pages.https://doi.org/10.1145/3472883.3486980

1 INTRODUCTION
Data analytics is never a one-person job. Analysts working on the same dataset collaborate [4, 19, 20, 29, 41] in cleaning, transforming, and manipulating data. However, conventional wisdom from collaborative software development (e.g., Git) suggests that collaboration is better in an offline way, i.e., mainly on disconnected copies of data without any real-time coordination with a central server. In the same spirit, we argue collaborative data science should also be offline. Beyond the obvious scalability benefits from the elimination of centralized coordination [49], a user can work at her own pace and use any data wrangling/analytical software that she prefers, without interruption from other concurrent users, high latency from excessive real-time data transmission, or potential availability issues (e.g., those associated with keeping a live connection). Like with Git, after a user is done, it is her responsibility to push changes to the primary repository and merge these changes with any changes to the dataset that happened in the interim. Unfortunately, we find that existing dataset versioning systems [10, 28, 37, 53] crucially lack support for offline versioning.

We present a system, MindPalace, to facilitate such a workflow. MindPalace is a collaborative distributed versioned data system (DVDS) that implements such an offline versioning system. MindPalace supports a clone operation that makes a physical copy of a desired dataset. Users can modify (i.e., issue SQL UPDATEs on individual or batches of tuples) independent and disconnected copies offline, and then later merge branches (analogous to a branch merging in Git). A merge involves two major steps: automated detection of conflicts (i.e., those data that cannot be merged automatically by the system) amongst different branches and reconciliation of identified conflicts (which will require user interaction). While our target application is collaborative analytics, the ideas are applicable to a variety of systems or applications that support partial asynchronous replication.

The key contribution of MindPalace is an algorithmic framework to implement the most critical step of offline DVDS, the merge feature. We identify problems (“conflicts”) a merge may encounter, and demonstrate a framework for identifying and resolving them based on a new formal property that we call auto-mergeability. Informally, two branches are auto-mergeable if the system can merge them without a user’s intervention. Specifically, auto-mergeability requires that a final database state does not depend on the choice of interleaving of operations, or a total ordering of two branches’ modifications that respects local orderings. While users’ or applications’ demands may differ, we find that our formulation of identifying and dealing with conflicts is more than sufficient for a variety of use cases. We discuss the benefits of such a scheme in Section 2.2.

We contribute an efficient algorithm to detect conflicts of auto-mergeability in two branches. It considers a branch as a sequence of logical modifications (i.e., UPDATE statements) instead of a set of physical record operations (i.e., ‘change line 357 from Revision to Accept’), which prior data versioning systems [28, 37, 53] and diff-based method rely on. Logical update tracking is highly efficient, as it avoids transferring large volumes of data across machines to perform a merge. Moreover, in analyzing logical semantics of modifications to identify precise conditions on conflicting data, our algorithm minimizes the number of time-consuming physical database operations. Besides the efficiency gain, logical

∗Work was done mainly when the author was at the University of Chicago.
tracking allows for reasoning about scenarios where analysts wish to manipulate partial copies of a dataset (e.g., a random sample) and capture intentions via predicates (e.g., change all ‘US’ to ‘USA’). While partial copies may not physically overlap, users’ operations may still conflict on records in the primary dataset that were not in the partial replicas.

When two branches are not auto-mergeable, they need additional user input to resolve identified conflicts. However, it is almost infeasible to do so manually, as the number of valid interleavings grows exponentially in the number of modifications. We propose an interaction framework that gradually reconciles versions, terminating once the remaining unreconciled portions of the histories are auto-mergeable. In every iteration, we only ask users to choose a preferred order between two modifications. Ultimately, the version reconciliation procedure proposed is designed to optimize for 1) clarity, by identifying precisely which records are in conflict and reproducing them for the user’s reference; 2) conciseness, by aiming to minimize the amount of human input demanded; and 3) simplicity, by only presenting manageable decisions to users when input is required.

In summary, MindPalace provides users with a principled and scalable way to merge data updates. We present four major technical contributions. First, we analyze and formalize the problem of automatic merging. We define auto-mergeability as a necessary condition of merging without intervention. Second, we propose a scalable and efficient system, MindPalace, to detect auto-mergeability and identify non-auto-mergeable tuples if any. Third, we propose a resolution framework that presents pairwise prompts to a user to reconcile non-auto-mergeable versions. It prioritizes resolution of “early” conflicts, thus avoiding potential redundancies. Fourth, we implement MindPalace as an auxiliary client to PostgreSQL and compare it to alternative approaches. MindPalace supports a wide range of UPDATEs, INSERTs, and DELETEs (see Section 4.3 for details). In many diverse scenarios, MindPalace performs better, both in identifying a tight set of conflicting records and in total runtime.

2 MOTIVATION AND OVERVIEW
In this section, we start with a motivating example, discuss the desired properties of a version merging system, and introduce a proposed model of user interaction with a DVDS.

2.1 Motivating Example
We discuss a setting where two users collaborate in cleaning and preparing data. Two data analysts, Alvarez and Bano, work on an energy dataset (Table 1a) to build their ML model. The dataset records annual electricity consumption, population, city name, state, and other relevant information for every city. Upon downloading the data, Alvarez immediately notices that in all California cities there is a critical mistake: electricity consumption was reported in TWh instead of GWh. To fix this, he multiplies all data in this column by 1000 (A1: UPDATE SET Electricity = Electricity × 1000 WHERE State = ‘CA’). He then decides that small suburbs are not the focus of their analysis and issues (A2: DELETE FROM Table WHERE Population < 0.2). Finally, he uploads all his updates from this session (Table 1b). Meanwhile, after downloading a local copy of the data Bano notices that several cities’ electricity data are invalid as 0, and fills them with data from other sources (B1: UPDATE SET Electricity = 9 WHERE City = ‘San Jose’; B2: UPDATE SET Electricity = 0.4 WHERE City = ‘Burbank’). After that, she realizes that the cities with low energy consumption per capita would be outliers for their analytics and issues the command (B3: DELETE FROM Table WHERE Electricity / Population < 10). Upon uploading her modifications (Table 1c), she notices that a merge was needed with Alvarez’s committed modifications.

In this example, both users had two “phases” of work: each fixed the data in the first few modifications (A1, B1, and B2), and prepared the data in the subsequent modifications (A2 and B3). Ideally, the data fixing operations should happen before the preparation ones, so one of the desired ways to reconcile them is to apply operations on data in the order of \{B1, B2, A1, A2, B3\} (Table 1d). We emphasize that if the operations are not performed in an ideal order, undesirable final states of data occur: for example, simply concatenating both users’ modifications in a serial order, i.e. \{A1, A2, B1, B2, B3\} (or even \{B1, B2, B3, A1, A2\}) incorrectly removes San Jose from the dataset (Table 1e).
Table 1: Visualization of Example 2.1. Merging two branches (1b and 1c) requires careful inspection (1d); arbitrary or default reconciliation may cause data corruption (1e). Names of cities are abbreviated in subsequent tables.

| (a) The Initial Dataset | (b) After Alvarez’s Updates | (c) After Bano’s Updates | (d) After \{B_1, B_2, A_1, A_2, B_3\} | (e) After \{A_1, A_2, B_1, B_2, B_3\} |
|-------------------------|----------------------------|-------------------------|--------------------------------------|--------------------------------------|
| Name | State | Population (M) | Electricity (GWh) | Name | State | Pop | Elec | Name | State | Pop | Elec |
| Los Angeles | CA | 3.2 | 43 |
| Seattle | D.C. | 0.6 | 8,709 |
| Burbank | CA | 0.1 | 0 |
| San Jose | CA | 1.0 | 9,000 |

State of the data post-merge depends on which merging strategies were allowed [16] and which one was chosen. Git automatically merges if there are no conflicting lines and demands manual line-by-line merging otherwise.

We argue that for datasets, defining a valid merge as a total ordering of all modifications while preserving the local orders among each user’s modifications is suitable for many settings (in data science and beyond). For instance, valid merges of the modifications in Example 2.1 (total orderings) might include \{A_1, A_2, B_1, B_2, B_3\} or \{B_1, A_1, A_2, B_2, B_3\}, but not \{A_2, A_1, B_2, B_1, B_3\}. This definition has multiple advantages. First, modeling the modifications as logical operations (e.g., SQL UPDATE statements) instead of physical records (i.e., reads and writes) captures dependencies between different users’ updates that may not be reflected just by examining the data itself. Unlike Git or Google Sheets, which just examines the physical writes, logical operations capture precise read-write dependencies. Second, by finding a total order for all the updates (e.g., as opposed to a merging strategy that just deletes updates until no conflicts exist anymore), it represents the modifications of users as much as possible. Third, by mandating that total orders respect local orders, it guarantees a user that her updates appear in the order she issued them. In doing so, the offline versioning system retroactively emulates an online centralized system with concurrent updates from multiple users. Finally, this formulation allows for a lightweight, fine-grained resolution of conflicts. In the above example, if it turns out that Alvarez’s and Bano’s modifications conflict, often just specifying a few simple constraints such as “A_1 must precede B_1” suffices in resolving all conflicts (to be discussed in greater detail in future Section 5).

We again emphasize that the merging framework outlined in this section need not be the only valid framework for merging updates. It is one such framework that provides guarantees commonly needed in a variety of settings. The rest of this paper will offer solutions to the challenges (namely detecting and resolving conflicts) under this framework.

### 2.3 DVDS Overview

A DVDS must support certain fundamental Git-like operations. A clone creates a remote physical copy of a dataset repository locally. Since the dataset can be large, a user may specify which portions of the dataset of which he wishes to clone, such as a random sample. A user can perform a sequence of atomic changes, or commits, to a local dataset. For simplicity, in this paper we assume each commit contains one SQL UPDATE statement. A commit could change individual tuple, or perform batch modifications, e.g., ”change all US to USA”. We emphasize that like Git, the local commits are visible to nobody except the local user until they are pushed. A push uploads one or more commits to the primary repository. When pushing commits to the primary repository, a merge must occur if there are concurrent commits. If there are multiple concurrent branches, a merge must occur every time the user merges one branch to the master, or merges two branches. Depending on the context, this operation may be restricted to users with administrative privileges.

### 3 AUTO-MERGEABILITY

First, we formally define auto-mergeability, and explain how this definition is crucial for reliable reconciliation in a DVDS.
3.1 Property Definition

Auto-mergeability is a property of two users’ update histories. It stipulates that all possible interleavings of the operations in those histories result in the same final database state. Let \( \phi(\cdot) \) denote a single modification operation to a dataset \( D \). We call an ordered sequence of modifications a history \( H = \phi_1 \phi_2 \cdots \phi_m \). The application of this sequence of updates to a dataset results in a final state of a history \( H \):

\[
D_H = \phi_m(\ldots \phi_2(\phi_1(D)))
\]

(1)

Table 2 contains all of notation and terminology that we use throughout the paper.

If we have two different users who are modifying the data repository at the same time without synchronization, they will naturally have two different histories \( H_1 \) and \( H_2 \) that form two branches. An interleaving is a combined history that contains all of the operations in \( H_1 \) and \( H_2 \) and orders them in a way that respects the local ordering. Namely, for two histories \( H_1 = \phi_1 \phi_2 \cdots \phi_m \) and \( H_2 = \psi_1 \psi_2 \cdots \psi_n \), an interleaving is a combined history \( H \) such that: for \( i < j \), \( \phi_i < \phi_j \) in \( H \), and for \( i < j \), \( \psi_i < \psi_j \) in \( H \).

It is worth making a few remarks on this definition. First, interleaving is a class of version reconciliation operations that combines all of the two users modifications into a single sequence of operations (another history), with the constraint that the sequence must respect each history’s order of operations. This definition excludes any semantic forms of reconciliation that might combine operations from both histories or ignore duplicated ones. Under this model of reconciliation, auto-mergeability is a powerful concept. If it holds, manual reconciliation of two histories is not needed because any interleaving results in the same final state. Likewise, if it doesn’t hold, some manual intervention is required because there is at least some ambiguity about the final state.

**Auto-mergeability Definition**

A pair of modification histories \( H_1 \) and \( H_2 \) are auto-mergeable if and only if all interleavings produce result in same final database state.

Furthermore, while intuitive, it is actually unclear how to test for auto-mergeability. The exhaustive solution to the auto-mergeability problem—simply permuting all valid interleavings and verifying they produce the same result—has an impractical time complexity, with the number of interleavings growing with \( C(m + n, n) \), where \( m \) and \( n \) are the sizes of two modification histories. This number is \( 1.2 \times 10^{17} \) when \( n \) and \( m \) are just 30. Accordingly, the core contribution of this paper is an efficient algorithm that detects conflicts using pairwise comparisons between modifications.

3.2 Conflict Identification and Reconciliation

The auto-mergeability definition in the previous section can be leveraged to design the reconciliation workflow of a DVDS. Auto-mergeability can alternatively be defined in terms of individual tuples in the original dataset. We define a set of tuples \( C_t \subset D_0 \) as auto-mergeability conflicts if \( H_1 \) and \( H_2 \) are auto-mergeable over \( D_0 \setminus C_t \). Naturally, \( H_1 \) and \( H_2 \) are auto-mergeable if and only if no tuples are conflicting tuples. The definition of tuple-level auto-mergeability conflicts gives us a finer-grained objective than simply determining if \( H_1 \) and \( H_2 \) are auto-mergeable. It is these conflicts that will allow a user to determine how to reconcile two non-auto-mergeable histories because she can pinpoint the particular tuples whose final state is ambiguous. Therefore, an ideal DVDS should identify the conflicting tuples as precisely as possible.

There are interesting precision and recall considerations in detecting conflicting tuples. Two types of errors may manifest: false positives (identifying auto-mergeable tuples as non-auto-mergeable) and false negatives (identifying non-auto-mergeable tuples as auto-mergeable). False negatives must be avoided, as trusting a record by mistake could cause severe issues to following data analytics: for instance, in Example 2.1, a user will not even be aware of the loss of the San Jose record if the DVDS incorrectly believes the modifications are auto-mergeable and arbitrarily chooses to apply the serial order in Table 1e. False positives do not compromise the integrity of a database or cause cascading errors, but they are not harmless: the system has to demand manual user reconciliation when it is in fact unnecessary. MindPalace tries to identify \( C_t \) efficiently without losing accuracy: it returns a \( C'_t \) with a guarantee of no false negatives (i.e., \( T 

\[ |C'_t \setminus C_t| \] is small).

Any reconciliation process involving a human must be relatively lightweight. For this reason, we believe that asking a user to determine a total order of all possible modifications is infeasible (the number of valid interleavings is exponential in the number of modifications), as is having her choose among a desired version for every conflict tuple. Instead, we ask a series of questions that only requires her to specify the relative order of two modifications from two histories. We discuss our reconciliation workflow in Section 5.

**Integrity Constraints:** Auto-mergeability is naturally compatible with database integrity constraints. If a set of histories is auto-mergeable, then a user may use integrity-checking mechanisms to verify that one interleaving, e.g., a serial ordering, does preserve integrity constraints, and conclude that every interleaving preserves constraints. Similarly, if the arbitrarily chosen interleaving is not constraint-preserving,
one can assert that none of the possible interleaving (of an auto-mergeable history) is constraint-preserving.

**Conflicts and Incompatible Reads/Write:** Locking schemes are a hallmark of transaction processing that detect “conflicts” in a concurrent environment and can be utilized to detect non-auto-mergeable tuples as those accessed by incompatible locks. However, even with the finest granularity (i.e., cell-level locks), they still incur high false positives. Consider Example 2.1: while all California cities have incompatible locks (written by A1 and read by B3), only San Jose is in conflict. Los Angeles is auto-mergeable because B3 will not delete it if its electricity is no less than 32 (population \(10\)), which is true before or after A1. As with this example, a leading reason for why locking schemes are ineffective in the auto-mergeability problem is because they are only concerned with whether read/write happens and not the values read/written. Advanced lock schemes that consider values, including semantic locks \([30]\), cannot completely mitigate the high false positive rate as they lack mechanisms to efficiently enumerate which modifications from the other history happen prior to the lock, and whether the final result would be the same.

More importantly, locking schemes are highly inefficient. A necessary prerequisite of any physical locking schemes is materialization of modifications. Specifically, for a history \(\phi_1\phi_2\ldots\phi_m\), we need to execute \(\phi_1\ldots\phi_{i-1}\) on data \(D\) before we know exactly which records are being locked by \(\phi_i\). In order to compare lock compatibility from different users, we need to either ship locking records from users (which could be as huge as the data itself), or ship modification logs and re-execute them (on a centralized server or one user’s local environment). Both ways incur high overhead.

## 4 CONFLICT DETECTION

In this Section, we propose an algorithm that determines whether two histories are auto-mergeable, and identifies conflicting tuples if not.

### 4.1 Pairwise Conflict Detection

Our key insight is an important important sufficient condition of auto-mergeability. If all pairs of modifications from two histories are commutative (we will be more precise in the next paragraph), then two histories are auto-mergeable. This theorem opens up the opportunity for efficient conflict detection algorithms: instead of enumerating all possible interleavings of two histories, we only need to examine all pairs of modifications from two histories, which has a polynomial complexity.

Commutativity means that the order of modifications does not matter (at least over the data present in the database). Let \(\phi\) and \(\psi\) be two modification operations. For any tuple \(t\), we can define \(\phi(\psi(t))\) (applying \(\phi\) and \(\psi\)) and \(\psi(\phi(t))\) (vice versa). We say that \(\phi\) and \(\psi\) are commutative if and only if \(\phi(\psi(t)) \equiv \psi(\phi(t))\) over all tuples in a database \(D\). Conversely, they are commutative (or “conflict”) on a database version \(D\) if \(\phi(\psi(t)) \neq \psi(\phi(t))\) on at least a tuple \(t\) in \(D\).

To leverage commutativity, we need to define some manipulations over histories. We denote \(\text{pref}_\ell(H)\) as the first \(k\) modifications from \(H\) (note that \(\text{pref}_0(H) = \emptyset\)), and denote concatenation of two histories by putting one after another. i.e., \(H_1H_2\) represents the modifications of \(H_1\) followed by the modifications of \(H_2\). Armed with these definitions, we arrive at the following theorem.

**Theorem 1:** Two histories \(H_1\) and \(H_2\) are auto-mergeable if there does not exist \(i, j\) such that \(\phi_i \in H_1, \psi_j \in H_2\) conflict (are non-commutative) on the database version \(D_{\text{pref}_{i-1}(H_1)\text{pref}_{j-1}(H_2)}\).

**Proof:** For \(H_1\) and \(H_2\), auto-mergeability means that for every pair of valid interleavings \(\Pi\) and \(\Pi'\), we have \(D_{\Pi} = D_{\Pi'}\). We will prove this by showing that for any valid interleaving \(\Pi, D_{\Pi} = D_{H_1H_2}\).

We will prove that these exist a sequence of interleavings \(\Pi_1, \Pi_2, \ldots, \Pi_p\) such that \(\Pi_1 = \Pi, \Pi_p = H_1H_2,\) and \(D_{\Pi_i} = D_{\Pi_{i+1}}\) for all \(1 \leq i \leq p - 1\). This sequence is a result of “swapping” modifications. Intuitively speaking, we first find \(\phi_1\) from \(H_1\), move it to left as much as possible: each step we swap it with its left neighbor from \(H_2\). Then we find \(\phi_2\) and repeat the swapping procedure. After all moves finish, the interleaving becomes \(H_1H_2\) (the serial ordering).

A critical step of this proof is to demonstrate that the two interleavings before and after a swap produce the same result on \(D\). Assume \(\phi_i \in H_1\) is the leftmost modification that is not on the left of all modifications from \(H_2\). Formally speaking, suppose \(\Pi \neq H_1H_2\) and

\[
\Pi = \text{pref}_{i-1}(H_1) \text{pref}_{j-1}(H_2) \psi_{i} \psi_{i+1} \ldots \psi_{j} \psi_{j+1} \ldots \psi_{p}
\]

where \(\Pi_S\) is any arbitrary valid interleavings of the suffix (i.e., remaining modifications in \(H_1\) and \(H_2\)). By swapping \(\phi_i\) and \(\psi_j\), we have obtained a new interleaving

\[
\Pi' = \text{pref}_{i-1}(H_1) \text{pref}_{j-1}(H_2) \psi_{i} \psi_{j} \psi_{i+1} \ldots \psi_{j+1} \ldots \psi_{p}
\]

We know that \(D_{\Pi} = D_{\Pi'}\), since from the assumption, we have

\[
D_{\text{pref}_{i-1}(H_1) \text{pref}_{j-1}(H_2) \psi_{i} \psi_{j}} = D_{\text{pref}_{i-1}(H_1) \text{pref}_{j-1}(H_2) \psi_{j} \psi_{i}}
\]

and executing \(\Pi_S\) after at the same database gives same result. \(\square\)

**Remarks:** It is important to note that Theorem 1 is sufficient but not necessary. One extreme example where this is the case is when the last modifications of \(H_1\) and \(H_2\) delete the database. Here, \(H_1\) and \(H_2\) are auto-mergeable (the database is empty regardless of the specific interleaving) regardless of any prior pair of conflicting modifications. In general, when two modifications conflict and Theorem 1 reports the histories as non-auto-mergeable, a late modification from
one user may nullify the inconsistencies caused by conflict modifications and makes the database auto-mergeable. However, we believe that false positives are uncommon, for a few reasons. First, it is possible that there exist multiple pairs of modifications that conflict on \( t \), so even if the effect of one is moot, the tuple still has attributes that are non-auto-mergeable. Second, only the effect of a read-write conflict (see Section 4.2.1) can be overwritten without triggering another conflict. Third, inconsistencies in one attribute may breed further inconsistencies in other attributes. Thus, multiple modifications may be needed to overwrite these inconsistencies into a consistent state, which is unlikely. We empirically evaluate the amount of falsely reported conflicts under varying data and query parameters in Section 7.

4.2 Efficiently Detecting Pairwise Conflicts

A straightforward implementation of Theorem 1 is still not efficient enough, due to the huge space/time cost of building temporary data views (all \( D_{\text{pref}}(H_1) \cap \text{pref}(H_2) \)) and executing modifications. Instead of doing this check physically for each version, we reason about the conditions that conflicting tuples must satisfy. To do so, we first identify the first point in both histories at which conflicts arise \( D_{\text{pref}}(H_1) \cap \text{pref}(H_2) \), then “backtrack” the modifications, maintaining an equivalent condition for every version (in Section 4.2.2) until one that can be queried on the latest common ancestor \( D_0 \) is obtained. Finally, we execute the condition on \( D_0 \) to find all conflicting tuples.

In this section, we assume for simplicity of explanation that modifications read and write a single table and that modifications are of the form \( \text{UPDATE SET } B = b \text{ WHERE } A = a \), where \( A \) and \( B \) refer to columns (attributes) and \( a \) and \( b \) are literal values. Throughout the paper we use upper case letters for column names, and lower case letters for constant values. We use the equivalent notation \( Q : (A = a) \rightarrow (B = b) \) to represent the modification. When \( C \) is a condition, \( V(C) \) represents the tuples in \( V \) that satisfy \( C \). We denote by \( V[Q] \) the set of tuples in a database version \( V \) that are impacted by \( Q : (A = a) \rightarrow (B = b) \), i.e., \( V[A = a] \). Much of the theory presented in this paper applies to general deterministic modification functions, and we will discuss how to extend it to more complex modifications in Section 4.3.

4.2.1 Detecting Pairwise Conflicts. We emphasize that the following discussion assumes that we have known the actual version of data we work on (i.e., \( D_{\text{pref}}(H_1) \cap \text{pref}(H_2) \)). We relax this assumption in Section 4.2.2.

We determine whether two modifications, \( \phi \) and \( \psi \), are commutative on a version of a database \( D \). A naïve solution simply entails materializing the two possible interleavings \( \phi(\psi(D)) \) and \( \psi(\phi(D)) \) and checking if there are differences. To avoid overheads with actually executing modifications and materialization, we instead deduce logical conditions that non-commutative tuples (i.e., tuples \( t \in D \) such that \( \phi(\psi(t)) \neq \psi(\phi(t)) \)) must satisfy. This provides two major advantages. First, it provides a succinct summary of what parts of the data are not commutative. Second, it allows for optimizations outlined in Section 4.2.2.

The names given to types of conflicts (e.g. `write-write`) that we look for are analogous to similar concepts defined in traditional transaction processing/locking theory. However, we emphasize that the concepts we describe are more precise and identify a tuple as conflicting if and only if the tuple is non-commutative, while traditional definitions are sufficient but not necessary in detecting non-commutativity.

To revisit a previous example, if two modifications both conditionally write to the same tuple, traditional locking theory identifies the tuple as conflicting, whereas the methods we propose inspects whether the conditions are satisfied.

**Commutative Condition Problem**

Find conditions on a tuple \( t \) under which \( \phi(\psi(t)) = \psi(\phi(t)) \), given \( \phi : A = a \rightarrow B = b \) and \( \psi : K = k \rightarrow L := 1. \)

In following discussions, we highlight the conditions of two types conflicts as **blue** or **red**. These must be true regardless whether the modifications have simple predicates (e.g., \( A = a \)) or complex conditions (on \( A \) or more attributes). We show how to directly check them when the predicates are in simple form, in **bold**.

**Write-write conflicts:** We know that for the pair of modifications \( \phi \) and \( \psi \), a write-write conflict occurs on tuple \( t \) if and only if we have \( \emptyset_B = \emptyset \) (otherwise the modifications cannot possibly write the same cell of data), \( \emptyset_B \neq 1 \) (otherwise the modifications applied by both are equivalent, and order of application does not matter), and one of the following conditions:

- **Fixed**: \( \emptyset_t \in D[\phi] \cap D[\psi] \): If a tuple \( t \) is affected by both modifications after the other has been applied, then attribute \( B = L \) of \( t \) will see different values depending on which order of modifications is executed.
- **Other**: \( \emptyset_t \in (D[\phi] \cap D[\psi] \cap (D[\phi] \cap D[\psi])) \): If both modifications are never executed after the other is applied (e.g. \( \phi : (S = s_1) \rightarrow (S := 2) \) and \( \phi : (S = s_1) \rightarrow (S := s_3) \) with \( s_1 \neq s_2 \neq s_3 \)), then again attribute \( B = L \) will see different values depending on which order is executed. Note that this condition can often be neglected, since a tuple can only satisfy this condition if both modifications read and write the exact same single attribute (in this example, only if \( A = B = K = L \)).
we will show how to check $t \in D_{\phi}$. The symmetrical case is similar.

(1) If $A \neq L$, then $\psi$ does not alter the tuples touched by $\phi$.
Namely, this means $D_{\psi}[\phi] = D[\phi]$. Then $t \in D_{\psi}[\phi]$ if and only if $t \in D[\phi]$, which in turn means $t.A = a$.

(2) If $A = L$, then $\psi$ does change tuples touched by $\phi$, and we know:
(a) If $a = 1$, all $t$ satisfying $(t.K = k)$ on the original version $D$—regardless of whether they satisfied $(t.A = a)$ on $D$—will satisfy $(t.A = a)$ on version $D_{\psi}$. Specifically, we can conclude $D_{\psi}[\phi] = D[\phi] \cup \{D[t] \mid t = D_{\psi}[\phi] \}$, so $t \in D_{\psi}[\phi]$ means $(t.A = a) \land \lnot(t.K = k)$.
(b) If $a \neq 1$, all $t$ satisfying $(t.K = k)$ on the original version $D$—regardless of whether they satisfied $(t.A = a)$ on $D$—must not satisfy $(t.A = a)$ on version $D_{\psi}$. More specifically, we can conclude $D_{\psi}[\phi] = D[\phi] \setminus \{D[t] \mid t = D_{\psi}[\phi] \}$, and therefore $t \in D_{\psi}[\phi]$ is equivalent to having $(t.A = a) \lor \lnot(t.K = k)$.

**Example 4.1.** Consider the following two queries issued on the same database $D$ from Example 2.1:

$\phi$: UPDATE db SET Population = 5 WHERE City = 'Seattle' -- not in DC

$\psi$: UPDATE db SET State = 'DC' WHERE State = 'D.C.'

To find tuples where there is a write-write conflict, we have $\emptyset B = L = \text{State}$, and $\emptyset b = \text{WA} \neq \text{DC} = 1$, so we must check that $\emptyset t \in D_{\psi}[\phi] \cap D_{\psi}[\psi]$ holds. (Note that we do not have to check $\emptyset$ since $\phi$ does not read and write the same single attribute.) For $t \in D_{\psi}[\phi]$, by rule (1) described previously, this is equivalent to checking the condition $(t.\text{City} = \text{Seattle})$. For $t \in D_{\psi}[\psi]$, by rule (2)(b), we check the condition $(t.\text{State} = \text{DC}) \land \lnot(t.\text{City} = \text{Seattle})$. We conjoint the two conditions to obtain $(t.\text{City} = \text{Seattle}) \lor (t.\text{State} = \text{DC}) \land \lnot(t.\text{City} = \text{Seattle})$, which is not satisfiable; hence, no data is in conflict.

**Read-write conflicts:** We define a read-write conflict between $\phi: A = k \rightarrow B = b$ and $\psi: K = k \rightarrow L = l$ as a conflict that occurs because $\phi$ reads an attribute that $\psi$ writes. We will refer to the reverse case hereinafter as a write-read conflict, which can be handled similarly. For a read-write conflict between $\phi$ and $\psi$ to occur on some tuple $t$, we must have that $\emptyset B = L$ and $\emptyset b = b$ (otherwise $\phi$ does not actually change the value of $t.B$), and $\emptyset t \in D[\phi] \Delta D_{\psi}[\phi]$ (i.e., $\psi$ changes whether $t$ will be updated by $\phi$; $\Delta$ denotes the set symmetric difference. Condition 4 can be checked against query semantics, and $\emptyset$ is already in the form apt for database querying. We demonstrate how to evaluate $\emptyset$:

(1) We must have $t.K = k$, otherwise $t \notin D[\psi]$, so the modification applied by $\psi$ does not affect $t$: namely, $\psi(t) = t$.

In other words, whether the modification $\phi$ applies to $t$ doesn’t depend on when $\psi$ is executed. (i.e., $t \in D[\phi] \cap D_{\psi}[\phi]$).

(2) Logic dictates that $\emptyset t \in D[\phi] \Delta D_{\psi}[\phi]$ implies either:
(a) $t \in D[\phi] \setminus D_{\psi}[\phi]$, or in other words, the application of $\psi$ removed $t$ from the set of tuples that $\phi$ affects.
This is only possible if $t.A = a$ and $a \neq 1$.
(b) Or $t \in D_{\psi}[\phi] \setminus D[\phi]$, or in other words, the application of $\psi$ included $t$ in the set of tuples that $\phi$ affects.
This is only possible if $t.A \neq a$ and $a = 1$.

**Example 4.2.** Consider the following two queries issued on the same database $D$ from Example 2.1:

$\phi$: UPDATE db SET Population = 5 WHERE City = 'Los Angeles' -- new data

$\psi$: UPDATE db SET City = 'Los Angeles' WHERE City = 'Los Angeles' -- fix a typo

Upon inspection of semantics, we note $\emptyset B = L$ is satisfied. Any tuple $t$ in conflict must have $\emptyset t.B \neq b$, i.e., Population $\neq 5$. To check if there is any $\emptyset t \in D[\phi] \Delta D_{\psi}[\phi]$, according to rule (1) we must have $t.\text{City} = \text{Los Angeles}$, and since we have $a = \text{Los Angeles} = 1$, the logic in part (2)(b) dictates that the equivalent condition to be checked is $t.\text{City} = \text{Los Angeles}$. We conjoint these conditions to obtain (note the last condition is implied by the second so we can omit it): $(t.\text{Population} \neq 5) \land (t.\text{City} = \text{Los Angeles})$

Upon querying the database (ib) with this condition, we find that one tuple is in conflict.

We prove that the lack of the two types of conflict we discuss previously indicates that two modifications are commutative. We reiterate that the traditional transaction processing theory does not help here: although the end goal of determining commutativity is similar, the conflict types we propose are much “narrower” than the similar concepts from transaction processing theory.

**Lemma 1:** If $t \notin R_D(\phi) \cup R_D'(\phi)$ or $t \notin R_D(\psi) \cup R_D'(\psi)$, then $\phi(\psi(t)) = \psi(\phi(t))$.

**Proof:** This can be intuitively described as one of the updates never affecting $t$, regardless of whether the other update is executed before. More formally, $t \notin R_D(\phi) \cup R_D(\psi)$ implies $\phi(\psi(t)) = \psi(t)$ and $\phi(t) = t$. These two, when put together, imply $\phi(\psi(t)) = \psi(\phi(t))$ and $\phi(t) = \psi(\phi(t))$. The same logic can be used to show that $t \notin R_D(\psi) \cup R_D'(\psi)$ also implies $\psi(\phi(t)) = \psi(\phi(t))$. □

**Theorem 2:** There is a write-write, read-write, or write-read conflict on tuple $t$ between $\phi: A = a \rightarrow B = b$ and $\psi: K = k \rightarrow L = l$, if and only if $\phi(\psi(t)) \neq \psi(\phi(t))$. 
Proof: Define three shorthand notations of sets that we will reference: Let $P = \mathcal{R}_{\phi_D}(\psi) \cap \mathcal{R}_{\psi_D}(\phi)$, $\Sigma = \mathcal{R}_D(\phi) \Delta \mathcal{R}_{\psi_D}(\phi)$, and $T = \mathcal{R}_D(\phi) \Delta \mathcal{R}_{\psi_D}(\phi)$. 

$(\Rightarrow)$ This direction is outlined on the previous discussion.

$(\Leftarrow)$ We will prove the contrapositive of this statement, namely that there are no conflicts. In other words, we will examine broader condition on $t$ where $\phi(\psi(t)) = \phi(\psi(t))$. In first-order logic, the assumption of no WW, RW, or WR conflicts on $t$ implies $\phi(\psi(t)) = \phi(\psi(t))$. That said, either $\phi$ or $\psi$ or both must be considered on broader condition on $t$, there must be some attributes of $t$ that are inconsistent. In fact, these attributes must be the subject of a write — either of $\phi$ or of $\psi$ — and are thus $B$ and $L$. With this fact, we will convert this logic into disjunctive normal form and consider each case, showing why it is sufficient in determining that there are no conflicts. In other words, we will examine all possible combination of $X \cap Y \cap Z$ while $X$ is one of $\mathcal{R}_D(\phi)$, $X$ is one of $\mathcal{R}_D(\phi) \cup \mathcal{R}_{\psi_D}(\phi)$, and $Z$ is one of $\mathcal{R}_D(\phi) \cup \mathcal{R}_{\psi_D}(\phi)$.

Before proceeding, we note that the condition $t \notin \Sigma$ is equivalent to the condition $(t \in \mathcal{R}_D(\phi) \cap \mathcal{R}_{\psi_D}(\phi)) \land (t \notin \mathcal{R}_D(\phi) \cup \mathcal{R}_{\psi_D}(\phi))$. The result of Lemma 1 shows it is sufficient to consider the case where $t \in \sigma$, with $\sigma = \mathcal{R}_D(\phi) \land \mathcal{R}_{\psi_D}(\phi)$. Similar logic shows it is sufficient to consider the case where $t \in \tau$, with $\tau = T = \mathcal{R}_D(\phi) \cup \mathcal{R}_{\psi_D}(\phi)$, in lieu of the broader condition $t \notin T$.

(1) If $\mathcal{O}(t.B = \beta) \land \mathcal{O}(t.L = \lambda)$, then $\phi$ and $\psi$ never actually change the values of $t.B$ or $t.L$, regardless of whether $t$ satisfies the predicates of $\phi$ and $\psi$. Therefore, we are guaranteed that after applying $\phi$ and $\psi$ in whatever order, $t.B = \beta$ and $t.L = \lambda$.

(2) $\mathcal{O}(t.B = \beta) \land (t \in \sigma) \land \mathcal{O}(t.L = \lambda)$: $B$ and $L$ are different attributes, and from $(t \in \sigma)$, we know that whichever ordering we have, $t$ undergoes the update $\phi$. Therefore, at the end of applying both $\phi$ and $\psi$, we are guaranteed $t.B = \beta$. Using similar logic as case (1), we know that $t.L = \lambda$ implies $\psi$ never changes the value of $t.L$; therefore, we conclude that regardless of whether $\psi$ was applied to $t$, we are guaranteed $t.L = \lambda$.

(3) $\mathcal{O}(t.B = \beta) \land (t \notin \sigma) \land \mathcal{O}(t \notin T)$: symmetric case to (2).

(4) $\mathcal{O}(t.B = \beta) \land (t \in \sigma) \land \mathcal{O}(t \in \tau)$: From $(t \in \sigma)$, we know that whichever ordering we have, $t$ undergoes the update $\phi$. From $(t \in \tau)$, we know that whichever ordering we have, $t$ undergoes the update $\psi$. Therefore, $B$ and $L$ being different attributes guarantees that after application of both updates we have $t.B = \beta$ and $t.L = \lambda$.

(5) $\mathcal{O}(\beta = \lambda) \land (t \in \sigma) \land \mathcal{O}(t.L = \lambda)$: if we do not have $B = L$, we recover case (2). From $(t \in \sigma)$ we know that $t$ must undergo the update $\phi$. If we choose the order $\psi$, then we are guaranteed that $t.B = t.L = \beta$. If we choose the order $\phi$, then immediately before $\psi$ is applied we have $(t.L = \lambda)$, so regardless of whether $\psi$ is applied, we are guaranteed that $t.B = \beta$. But since $t.B = t.L = \beta = \lambda$, there is no ambiguity and we are guaranteed $t.B = t.L = \lambda$.

(6) $\mathcal{O}(\beta = \lambda) \land \mathcal{O}(t.B = \beta) \land (t \in \tau)$: symmetric case to (5).

(7) $\mathcal{O}(\beta = \lambda) \land (t \in \sigma) \land \mathcal{O}(t \in \tau)$: from $(t \in \sigma)$ we know that $t$ must undergo the update $\phi$. Likewise, from $(t \in \tau)$, we know that whichever ordering we have, $t$ undergoes the update $\psi$. If $\psi$ is applied second, then it overwrites the update of $\psi$, and we are guaranteed $t.B = t.L = \beta$. Similarly, if $\psi$ is applied second, then it overwrites the update of $\phi$, and we are guaranteed $t.B = t.L = \lambda$. However, the condition $(\beta = \lambda)$ means there is no ambiguity, and guarantees $t.B = t.L = \beta = \lambda$.

(8) $\mathcal{O}(t \notin P) \land (t \in \sigma) \land (t \notin T)$: we must have $(B = L) \land (\beta \neq \lambda)$, otherwise we recover previous cases. The condition $(t \notin P)$ implies either $t \notin \mathcal{R}_{\phi_D}(\phi)$ or $t \notin \mathcal{R}_{\psi_D}(\phi)$.

(a) If $t \notin \mathcal{R}_{\phi_D}(\phi)$, this is a contradiction of $t \in \sigma$.

(b) If $t \notin \mathcal{R}_{\psi_D}(\phi)$, then the update of $\psi$ must if applied after $\phi$: namely, $\psi(t) = \phi(t)$. Since $t \in \sigma$ implies $t \in \mathcal{R}_D(\phi)$, we conclude that after order of updates $\phi$ is applied, we are guaranteed $t.B = t.L = \beta$. Additionally, we know $t \in \mathcal{R}_{\psi_D}(\phi)$, and we can conclude that after the order of updates $\psi$ is applied, $t.B = t.L = \lambda$.

Therefore, the updates must be commutative on $t$.

(9) $\mathcal{O}(t \notin P) \land (t.B = \beta) \land (t \in \tau)$: symmetric case to (8).

(10) $\mathcal{O}(t \notin P) \land (t \in \sigma) \land (t \in \tau)$: from before, the condition $(t \notin P)$ implies either $t \notin \mathcal{R}_{\phi_D}(\phi)$ or $t \notin \mathcal{R}_{\psi_D}(\phi)$.

If $t \notin \mathcal{R}_{\phi_D}(\phi)$, this contradicts the condition $(t \in \sigma)$. Similarly, if $t \notin \mathcal{R}_{\psi_D}(\phi)$, this contradicts the condition $(t \in \tau)$, so this case is not possible.

As established before, $t.B$ and $t.L$ are the only possible inconsistent fields that a tuple $t$ may have. We have shown in all cases, the values of the $t.B$ and $t.L$ are unambiguous, implying that these conditions are sufficient for pairwise commutativity. □

To reconcile every record subject to the conflict $(\phi_i, \psi_j)$, we simply perform a union of the possible types of conflicts: $S_{\phi_i, \psi_j} = \text{conflict}_{\mathcal{W}(\phi_i, \psi_j)} \sqcup \text{conflict}_{\mathcal{W}(\phi_i, \psi_j)} \sqcup \text{conflict}_{\mathcal{W}(\psi_j, \phi_i)}$ where $S_{\phi_i, \psi_j}$ is the total set of records subject to the conflict $(\phi_i, \psi_j)$. The result of theorem 1 allows us to say with confidence that any records not flagged as conflicted must be automergeable.

4.2.2 Condition Derivation via Backtracking. Though we have a condition (i.e., predicate) for all non-commutative tuples from an intermediate database version $D_H$ for some $H$, we
seek to avoid the costly process that executes $H$ on $D$ to materialize $D_H$. We "backtrack" the history $H$ as a sequence of modifications. At each step we consider the modification $\phi$: we have condition $C$ on data $D_\phi$, and our goal is to derive another condition $C'$ on $D$ such that $\phi(t) \in D_\phi[C]$ if and only if $t \in D[C']$. After the backtracking, we have a condition $C_0$ on the initial data $D_0$, and we evaluate $D_0[C_0]$.

This approach is significantly more efficient than the straightforward evaluation needed to materialize $D_H$. Evaluating $D_H$ requires updating all tuples involved in $H$ regardless whether these tuples are auto-mergeable or not. Instead, our approach defers evaluation on dataset as much as possible, and avoids the large overheads of updating data. Furthermore, if the final condition for conflict has a low selectivity, or even is unsatisfiable, we may further forego data evaluation costs. Our approach is especially efficient when data volumes are large—exactly the target scenario of DVDS.

Now we discuss the step of backtracking (building equivalent conditions on two versions of a database, separated by one modification). For the sake of exposition, we assume that we are trying to evaluate condition $C = f(c_1, c_2, \ldots)$, where all $c_i$ are simple equality conditions like $A = 10$, and $f$ is a logical function of the $c_i$ using AND, OR, and NOT. Note that this framework can be generalized to any complex logical conditions using whose axioms are state-independent; see Section 4.3. Based on the semantics of $\phi$, we change all $c_i$ to corresponding $c_i'$ such that $c_i'$ could be simple equality conditions or logic clauses (to be discussed as follows). We keep $f(\cdots)$ unchanged and denote $C' = f(c'_1, c'_2, \ldots)$. Our goal is that for any tuple $t \in D$, $c'_i(t) = c_i(\phi(t))$. Thus, $C'(t) = C(\phi(t))$, in other words, $t \in D[C']$ if any only if $\phi(t) \in D_\phi[C]$.

We now discuss how to construct an equivalent condition $c'_i$ for corresponding axiom $c_i$. Suppose $\phi : (B = b) \rightarrow (A = a)$, and $c_i : (K = k)$. We discuss the possible scenarios:

1. $\phi$ does not write attribute $K (A \neq K)$, then for any tuple $t$, its $K$ attribute is not modified. Therefore, we know $c'_i = c_i$.
2. $\phi$ writes attribute $A (A = K)$. In this case, there are two scenarios.
   a. If $a = k$, then $\phi(t)$ in $D_\phi$ may have been originally satisfied $c_i$ or its $K$ attribute may have been written by $\phi$, implying $(B = b)$. The new condition $c'_i$ is thus $(B = b) \lor c_i$.
   b. If $a \neq k$, then $\phi(t)$ must have satisfied $c_i$ already. Furthermore, it must not have been affected by $\phi$, necessarily meaning $(B \neq b)$. The new condition $c'_i$ is thus $\neg(B = b) \land c_i$.

**Example 4.3.** We have a condition $C$: $t.Population = 2000$ $\land$ $t.Electricity = 43000$ and wish to find the set $D_\phi[C]$ (i.e., all tuples which satisfy $C$ on the version of $D$ after application of modification $\phi$), where $\phi$ is $(City = 'Los Angeles') \rightarrow (Electricity = 43000)$.

Note that $t.Population = 2000$ is unaffected and the condition $t.Electricity = 43000$ becomes $t.Electricity = 43000 \lor t.City = 'Los Angeles' \land t.Population = 2000$. □

### 4.3 More General Query Model

Thus far, we have assumed queries of the form $Q : (A = a) \rightarrow (B = b)$ (in SQL, this can be represented as the query `UPDATE SET B = b WHERE A = a`). In this section, we consider generalizations to `INSERTs`, `DELETEs`, and complex `UPDATEs` including `JOINs`.

**Inserts and Deletes:** We treat inserts and deletes as special updates that either read or write `NULL` values. Specifically, we treat an insertion as an update writing a tuple with all attributes equal to `NULL` (and a special hidden unique ID) in the initial version of database $D_0$. Similarly, in handling a delete, we consider it as an update writing `NULL` values to an existing non-`NULL` tuple. We can make simplifications, as we will demonstrate, since we know `INSERTs` and `DELETEs` do not touch remaining dataset.

We will demonstrate these accommodations on an insert as an example. Suppose we have an insert $I$ and an update $U$ of the form

$I$: `INSERT VALUES (A = a_1, B = b_1, \ldots)`

$U$: `UPDATE db SET A = a_2 WHERE B = b_2`

To determine commutativity of $I$ and $U$ on version $V$, we note that only the “write-write” commutativity conditions must be checked on the tuple inserted by $I$, since $I$ does not touch other tuples. Applying the procedure from Section 4.1, we find that the updates are not commutative on the inserted tuple if and only if $(a_1 \neq a_2) \land (b_1 = b_2)$. (These updates commute on any other tuple.)

During the process of Condition Derivation (Section 4.2.2), when the algorithm "backtracks" to an insert statement, it evaluates all conditions on the newly inserted tuples, reports them as non-auto-mergeable if applicable, and continues as if the insert statement does not exist. This is because we assume the inserted tuples are all `NULLs` before the insertion, and all conditions evaluate to `FALSE` on `NULL` values. When the algorithm "backtracks" to a delete, it makes sure all deleted tuples are not being considered. Specifically, we note that $V_{del}[C'] = V[(C \land \neg CD)]$ where $del$ is the delete and $CD$ is the predicate of delete.

**Complex updates:** We discussed `UPDATEs` with simple predicates (i.e., attribute equals literal) and constant update values. In this section, we explain how to accommodate more complex predicates and updates that are well-represented
in everyday data analytics and also lend themselves to conflict backtracking (which is where most of MindPalace’s efficiency gains lie). We consider complex predicates that are state-independent, meaning that whether a tuple satisfies the condition does not depend on the state of other tuples. For example, \( A + B > C \) and \( A \in \{2, 3, 5\} \) are state-independent, but \( A \in \Pi_B(s(D)) \) is not if the database \( D \) is not held constant. Without loss of generality, we consider a modification’s predicate as a function \( f(A, B, \cdots) \) defined on its attributes. This predicate could include JOINs (on read-only relations), range queries, functional expressions (including UDFs), and set operation queries (IN, EXISTS, ALL, etc.) on read-only tables/sets. Note that any semi-JOIN can be made equivalent to an IN clause involving the JOIN attributes: for example, \( \text{UPDATE R SET A = a FROM R JOIN S on R.B = S.B} \) is equivalent to \( \text{UPDATE R SET A = a WHERE R.B IN (SELECT B from S)} \).

To determine commutativity between two such modifications, the procedure is no different from simple update. We still must check the same conditions for a read-write conflict and write-write conflict. Correctly evaluating conditions on versions of a database that have undergone modifications (e.g., \( t \in D_2[\varphi] \)) depends on the following Condition Derivation mechanism. Suppose we want to evaluate the condition \( C_2(A, B, \cdots) \) on database \( D' = \phi(D) \), while \( \phi \) is \( \text{UPDATE } dB \text{ SET } B = b \text{ WHERE } C_1(A, B, \cdots) \). As long as \( C_1 \) and \( C_2 \) are state-independent conditions, we can consider two cases: some tuple \( t \in D' \) satisfying \( C_2 \) could have: (i) \( t \) undergoes modification \( \phi \), and \( \phi(t) \) satisfies \( C_2 \), or (ii) \( t \) does not undergo modification \( \phi \), and \( t \) satisfies \( C_2 \). In other words, our newly built condition is:

\[
(\neg C_1(A, B, \cdots) \land C_2(A, B, \cdots)) \lor (C_1(A, B, \cdots) \land C_2(A, b, \cdots))
\]

Note that although MindPalace supports a wide range of complex queries in \( \text{UPDATEs, INSERTs, and DELETEs} \), their query evaluation time affects MindPalace’s efficiency. Two special cases allow further optimizations. First, if \( C_2 \) is independent of \( B \), then evaluating \( C_2 \) on \( D' \) is the same as evaluating \( C_2 \) on \( D \). Second, if either of \( C_1 \) or \( \neg C_1 \) is data-independent, we recover the simpler cases outlined in Section 4.1.

5 CONFLICT RESOLUTION

When non-auto-mergeable tuples exist, a user needs to resolve the conflicts and reconcile the versions. However, it is impractical for the user to manually specify a “correct” interleaving of modifications: for example, there are more than \( 10^{17} \) possible interleavings when both histories have 30 modifications. Instead, we present the use with an easier question: given two modifications, which should precede the other? MindPalace guides the user to a desired interleaving by repeatedly posing this question, together with a set of specific records for which the two modifications conflict to provide a concrete example he/she can reason through.

We present the formal algorithm in Algorithm 1. Similar with the conventional workflow from collaborative project management like Git, our framework merges two branches to form a new branch at one time. The conflict resolution works by iteratively finding the first operation pairs that cause a conflict. At each iteration, the resolution determines the “earliest” pair of conflicting modifications, and asks the user to specify the order between them. After that, the earlier one (and all preceding ones from the same history) is removed from the history, and is appended to the “finished” list (i.e., variable order). It terminates when at least one history is empty. Similar to Section 4.2.2, we virtually update \( D \) by Condition Derivation. It is not hard to see the number of user interactions is no more than the combined size of histories: each step of the loop asks the user to specify order at most once, and removes at least one modification from two histories. Thus, the loop body is executed at most \( |H_1| \times |H_2| \) times, upper-bounding the number of user-interactions. For comparison, the conventional algorithm that Git applies when merging two branches may ask the user to manually merge up to \( |H_1| \times |H_2| \) commits, as it is possible for every commit in \( H_1 \) to require manual merging with every commit in \( H_2 \).

The resolution is expressible in the way that it never prohibits the user from resolving in a certain interleaving. Formally, assume the user has a valid partial order \( \pi \) (of \( H_1 \) and \( H_2 \)) in her mind, and always answers questions posed by MindPalace consistent with the desired ordering. It can

---

**Algorithm 1:** Algorithm to resolve conflicts.

1. `function choose(\( \gamma, H, \text{sorted}, D \)):`
2. \[ D \leftarrow \gamma(D) \]
3. \[ \text{sorted} \leftarrow \text{sorted} \gamma \]
4. remove \( \gamma \) from \( H \)
5. `function resolution(H₁, H₂, D₀):`
6. \[ D \leftarrow D₀ \]
7. `order \leftarrow \emptyset`
8. `while H₁ ≠ \emptyset and H₂ ≠ \emptyset do`
9. \[ \phi \leftarrow H₁’s \text{ first element} \]
10. `if not found then`
11. \[ \text{choose}(\{ \phi \}, H₁, \text{order}, D) \]
12. `else`
13. `prompt user to resolve (\( \phi, \psi \))`
14. `if user specifies \( \phi < \psi \) then`
15. \[ \text{choose}(\{ \phi \}, H₁, \text{order}, D) \]
16. `else`
17. \[ \psi \leftarrow H₂’s \text{ op before } \psi \text{ (inclusive)} \]
18. \[ \text{choose}(\psi, H₂, \text{order}, D) \]
19. `return order H₁ H₂`
be shown that the resolution always returns an ordering \( \pi' \) that equivalent to \( \pi \) (i.e. \( \pi' \) and \( \pi \) yield the same final database state when applied).

**Lemma 3:** At any time of this algorithm execution process, \( \text{order} \) satisfies that \( \alpha \nless \beta \) (in \( \pi \)) for any \( \alpha \in \text{order} \) and \( \beta \notin \text{order} \).

**Proof:** The proof is by induction. Before the \( \text{while} \) loop this is certainly true since \( \text{order} \) is empty. In one step of the \( \text{while} \) loop, (i) if \( \psi \) is not found, we have \( \phi \nless \psi' \) for all \( \psi' \in H_2 \cap \text{order}^c \), thus adding \( \phi \) to \( \text{order} \) still obeys the condition specified in Lemma 3; (ii) if \( \psi \) is found and \( \phi < \psi \), we have \( \phi \nless \rho \) for \( \rho < \psi \) and \( \phi < \rho \) for \( \rho \geq \psi \), thus \( \phi \nless \rho \) for all \( \rho \in H_2 \cap \text{order}^c \), thus adding \( \phi \) to \( \text{order} \) still obeys the condition specified in Lemma 3; (iii) if \( \psi \) is found and \( \phi > \psi \), we have \( \psi' \leq \psi < \phi \leq \phi' \) for any \( \psi' \in \phi^+ \) and \( \phi' \in H_1 \cap \text{order}^c \), thus adding \( \psi^+ \) to \( \text{order} \) still obeys the condition specified in Lemma 3. \( \Box \)

**Theorem 4:** The returned value \( \pi' \) of Algorithm 1 is compatible with \( \pi \) (i.e., \( \pi \) is a subset of \( \pi' \)).

**Proof:** With Lemma 3, we prove the expressible claim by contradiction, then there exist two operations \( \alpha \) and \( \beta \) such that \( \alpha < \beta \) in \( \pi' \) and \( \alpha > \beta \) in \( \pi \). \( \alpha < \beta \) in \( \pi' \) means when \( \alpha \) is appended to \( \text{order} \), \( \beta \) is not appended to \( \text{order} \). Then the previous observation has \( \alpha \nless \beta \) in \( \pi \). This is the contradiction, so \( \pi' \) is always compatible with \( \pi \).

**Remarks:** It is important to emphasize that MindPalace is not a universal solution. Version reconciliation is a semantics-dependent problem: the correctness criteria depend on the application’s (or the user’s) specifications. As such, it is possible that MindPalace’s conflict resolution framework cannot yield a satisfactory result, either because the user faces a dilemma upon a question (e.g., both orders of a pair of modifications are undesirable) or the final order fails additional constraints upon termination. MindPalace automates an otherwise-manual process, where the user intends to find a desirable interleaving of two histories, but there is no guarantee that such an interleaving exists. Even when MindPalace fails to merge two histories, though, it can still provide valuable information: for example, if an interleaving that results from MindPalace’s version reconciliation violates integrity constraints, one can conclude that no interleaving can correctly preserve them. In such cases, reordering modifications doesn’t suffice, and users will have to resort to other merging mechanisms (e.g., removing or manually rewriting modifications), which are beyond the scope of this paper.

6 RELATED WORK

**Existing Versioning Work:** Systems that support versions have been developed for many different use cases and can take on many forms. DataHub [10] provides a central data repository that incorporates relevant SQL and versioning capabilities. As part of DataHub, Decibel [37] was a prototype centralized versioned-database to evaluate different physical designs and query execution strategies of versioned data. OrpheusDB [28] is a “bolt-on” centralized versioning system for relational databases, allowing users to store, track, and execute queries on different versions. Databricks Delta [18] is an industrial solution that can accommodate non-structured data, with special functionalities to streamline the analytics process. ForkBase [53] is a centralized DVDs that provides similar capabilities for applications that demand tamper evidence, and are of particular use in blockchains. Versioned databases and “GitHubs for Data” have been widely applied in industrial practice [4, 19, 20, 29, 41].

Although these systems support data versioning, their versioning control systems are all centralized in the way that users’ modifications are synchronized with a server all the time. Their conflict identification and version reconciliation rely heavily on human intervene, which quickly becomes infeasible as data grow. OrpheusDB and Decibel track conflicts by materializing updates and performing diffs on different versions. As discussed in the introduction, they suffer from several drawbacks. In the event of a conflict, they [28] offer some options for resolution, including a precedent ordering (a ranking of which updates are most important) or manual inspection of records. Databricks Delta [18] also adopts a data-centric conflict identification/resolution scheme by tracking changes via delta logs and maintaining versions corresponding to individual users’ modifications, in order to rollback modifications deemed to be in conflict with others.

**Conflict Avoidance:** In general, two approaches can ensure that a set of operations are conflict-free (i.e., conflicts are logically impossible, regardless of ordering). One approach is for a system to be conflict-free by design. Modifications expressed in these systems are always auto-mergeable. Conflict-Free Replicated Data Types (CRDT) [46] are conflict-free data types in a replicated environment. CALM [2, 3, 26] specifies a logical “monotonic” language that is guaranteed to be correct without coordination.

When modifications are not expressible in above systems, they may or may not be auto-mergeable (regardless of the specific instance of data). One approach to figure out is static program analysis, which analyzes the operations to be executed in a concurrent environment, and reasons about the correctness guarantee. Invariant confluence [5, 6, 57] and
IPA [7] study when the transaction processing is not necessary to preserve invariants. These mechanisms [1, 32, 43, 50, 52, 55] detect commutativity in two general programs. In the distributed environments, these approaches [7, 11, 13, 15, 21, 31, 34–36, 44, 48] reason about when a strong consistency is necessary, based on the semantics of the operations. Transaction checkpointing studies whether a transactions can be split into multiple smaller pieces that still guarantee serializability [47, 54, 61, 65]. Bernstein et al. [8] derive conditions that ensure the transactions are correct under each ANSI isolation level. Weihl [56] defines three properties on individual data that once enforced, will guarantee serializability.

Bounded staleness of divergent database replicas has also been explored [9, 23–25, 33, 39, 40, 42, 45, 58, 59, 62–64]. These approaches do not detect conflicts specifically, nor do they reason about the effects of individual modifications. Moreover, they may not satisfy the demand for DVDS snapshots to be exactly consistent.

Two modifications that are not auto-mergeable on all possible data (which could be determined by, say, some variant of a commutativity test) could still be auto-mergeable on a specific instance of data. MindPalace focuses on evaluating auto-mergeability on a specific instance of data, significantly relaxing restrictions on allowable API operations. Conversely, conflict-avoidance approaches often only offer a restrictive set of APIs for the user to express her modifications, and thus may be not practical in a DVDS setting, where it is likely that users will demand a richer set of capabilities when making their modifications. As such, a conflict management method that relies on restricting operation capabilities to predict/avoid conflicts is often not ideal.

**Merge and Fix:** Some merging and fixing approaches require user participation or only work on a situations that are naturally auto-mergeable, which in general we cannot assume to be the case in a collaborative setting. Unlike our approach, they cannot detect, nor do they reason about, the effects of conflicts. Doppel [38] reconciles branches on CRDT-like data types. Open nesting and transactional boosting [22, 27] allows users to specify compensate/inverse operations to roll back if the two branches are not mergable. Wu et al. [60] and Veldhuizen [51] speculatively execute the transactions without conflict detection/prevention, and then the fix the broken invariants if there is any exposed conflict. TARDiS [17] and Burckhardt et al. [12] allows a user to branch and merge. ConfluxDB [14] merges transactions executed in multiple snapshot isolation servers.

7 EXPERIMENTS

Our experimental study addresses two questions: (1) How does the accuracy and processing time of our proposed approach compare to alternatives in identifying non-auto-mergeable tuples, under various settings? (2) How reliant on human input is the version reconciliation algorithm for typical cases?

### 7.1 Experimental Setting

Our evaluations were performed on machines with dual socket Intel Xeon-E5 2650 processors (10 cores, 2.3 GHz each), 64 GB of RAM, and running Ubuntu 18.04. Without otherwise specified, all numbers are averaged based on 10 executions. As a simplification, all data is numerical, since the MindPalace’s accuracy in identifying conflicts does not depend on the data type and only depends on whether a cell is concurrently modified. All values are generated independently, with all values in the same column following the same distribution. The number of distinct values for each column range from 100 to 10^6, so as to incorporate a range of attribute selectivities.

**Alternative Approaches:** We compare our approach with a naïve ground truth and some alternative approaches:

- **Ground Truth:** We use a dynamic programming algorithm that tracks all possible outcomes of interleavings. For every tuple \( t \in D \), we track the set of possible tuple \( T_{i,j}(t) \) after a interleaving of \( \text{pref}_1(H_1) \) and \( \text{pref}_2(H_2) \) applies on \( t \). We have \( T_{i,j}(t) = \phi_i(T_{i-1,j}(t)) \cup \psi_j(T_{i,j-1}(t)) \). The tuple \( t \) is auto-mergeable iff \( |T_{i[j,H_1,H_2]}(t)| = 1 \). The worst case incurs the same complexity as enumerating all interleavings but this method runs faster in practice.

- **Compatible (Virtual) Locking:** We adopt locking schemes that help identifying conflicting tuples. The locks do not block modifications; they are for identifying non-auto-mergeable tuples. We report non-auto-mergeable tuples that are marked by non-compatible (i.e., read-write or write-write) requests from two histories. We have two locking schemes of different granularities, for the trade-off of costs and accuracy. For Record-Level, each tuple (record) has a lock; and for Cell-Level, each cell (data value) has a lock.

- **Git/Git-Like Diff Methods:** We benchmark three variants in Section 7.4. Vanilla Git (VG) simply runs `git merge` on the final committed states of two versions (dumped to text files) and flags any records in a conflict block as conflicting. Optimized Git (OG) improves on VG by ignoring records in conflict blocks whose final states were the same for both users. Record-Level 3-Way-Diff (RL3) executes three-way-diff logic on a record level, where a record is flagged as conflicting if its state in the original version and the two committed versions are each pairwise different.

**Online Dataset Versioning:** We benchmark OrpheusDB [28], a centralized system for dataset versioning. Once versions are committed, we issue an SQL three-way `JOIN` on the versioning metadata to identify conflicting records (using the same logical criterion as in the Record-Level 3-Way Diff method).
We vary five data/history parameters: (1) data skew (by varying the parameter \( \beta \) of a beta distribution), (2) history length, (3) selectivity, (4) number of columns, (5) size of the database.

### Implementation
MindPalace is implemented in Python. We store the database in a PostgreSQL 10 server, which executes queries on the database. The baselines are implemented by first tracking which physical tuples are read/written by each SQL update statement. Then, we flag those that were either written by both users or read by one and written by the other as conflicts.

Both the Vanilla Git and Optimized Git approaches use the `git merge` command on committed text versions of the dataset, annotating the database dump to identify conflicting blocks. A Python script parses the `git` annotations to identify non-auto-mergeable records (in the case of Optimized Git, it ignores records in conflict blocks with the same final state in both committed versions). To our knowledge, no existing `git` utility exactly implements the logic desired in the RL3 approach, so we use a Python script to identify conflicting records.

The online dataset versioning experiments used only OrpheusDB’s native commands (`checkout`, `commit`, `run`) to track conflicts. At the end, a SQL query was run on OrpheusDB’s versioning metadata to identify conflicting records. Orpheus stores versioning metadata, including which branches wrote which records, alongside the original dataset in an SQL database.

### Experiments: Simple Updates
We vary five data/history parameters: (1) data skew (by varying the parameter \( \beta \) of a beta distribution), (2) history length, (3) selectivity, (4) number of columns, (5) size of the database.
Figure 1a exhibits variation with different degrees of skewness. The decreasing proportion of conflicting tuples can be explained by the effective decrease in modification selectivity, as many data ranges are now more sparsely populated. In Figure 1b, we can observe that the more data is manipulated (i.e., applying more modifications), conflict rates become higher. Nonetheless, MindPalace adjusts seamlessly to the variations in all of these parameters, always identifying a tight set (with <1% relative margin of error) of tuples for reconciliation. In Figure 1c, we observe that skewing queries to select and modify more selective attributes (i.e., attributes with fewer distinct values in the domain) significantly increases the proportion of non-automergeable tuples in relation to the total database size, and vice-versa.

We display run times in Figure 2 against both increases in database size and history length (both of which when increased will produce higher runtimes for all approaches). The remaining parameters, when varied, do not impact runtime noticeably. We observe that the dynamic programming ground-truth algorithm requires orders of magnitude more time than MindPalace, due to its higher computational complexity. It needs hours to finish on a 1GB dataset and two histories with just 25 modifications, and thus it is hard to employ such an approach in the real world. The virtual locking schemes employed are relatively lightweight, with associated time increasing as the granularity of locking gets smaller (intuitively explained by the fact that there are now more locks to manage). MindPalace’s time-associated costs are comparable, if not better, than the locking-based approaches (which are already significantly faster than the ground-truth baseline and any “physical locking” approach).

7.3 Experiments: General Query Model
We also consider general modifications, as discussed in Section 4.3. Specifically, each user history contains INSERTs, DELETEs, and UPDATEs with complex predicates including range conditions, set containment, and JOIN clauses. These experiments were performed on the default parameters as discussed in Section 7.2. Inserts were either generated to be single-tuple inserts, or bulk inserts of 150,000 new tuples (each approx. 25 MB). Deletes were uniformly generated with equality or range predicates on randomly chosen attributes of the database. Joins with other tables were performed on primary key attributes. Complex predicates included complex logical conditions (e.g., conjunction), range conditions, and set containment queries (signified by keywords like IN, EXISTS, etc.). Each individual modification affects no more than 15% of the database. We illustrate the results in Figure 3.

In the first set of experiments, we vary ratios of query types while keeping the ratio of simple predicates to complex predicates at a constant 80/20 percentage ratio. We choose the percentage ratios of UPDATE/INSERT/DELETE as 100/0/0, 90/5/5, 75/20/5, and 50/40/10. In the second set of experiments, we maintain the ratio of UPDATE/INSERT/DELETE constant at 75/20/5, and vary the selection of simple predicates to complex predicates in the following ratios: 100/0, 90/10, 80/20, 70/30. In both experiments, we observe that as with the simple query experiments, MindPalace identifies a tight set of conflicting tuples that strays less than 1% from the true number. Note that the number of true positives has increased due to increased query selectivities of complex queries and that the number of false positives incurred by locking-based has grown disproportionately large. MindPalace’s computational time is comparable to those of locking-based approaches, and is orders-of-magnitude faster than the dynamic programming approach, which has suffered appropriately an order-of-magnitude increase in run time.

MindPalace runs more quickly as the number of INSERTs and DELETEs is increased. We believe that this occurs for two reasons: 1) querying inserted data is easier than querying already existing data since inserted data is smaller in size, and 2) the predicates that arise from handling conflicts with INSERTs and DELETEs are simpler than those involving UPDATEs. Second, MindPalace’s run time does not scale strongly with increases in the number of complex predicates.
7.4 Experiments: Diff-Based Methods

Next, we evaluate the accuracy and performance time of diff-based methods (i.e., the git-based methods and OrpheusDB). We use the parameters described in Section 7.2 (database width of 30, uniform selectivity, uniform data distributions, and a history length of 25).

As shown in Figure 4, diff-based methods fail to accurately identify auto-mergeable tuples. Vanilla Git identifies more than 10 times the true number of positives and even still may fail to flag all non-auto-mergeable records. Vanilla Git’s accuracy is a result of Git’s block-based conflict identification, which results in large blocks of conflicts being identified, even if most of the records in those blocks were untouched by both users. Optimized Git slightly improves upon Vanilla Git but still identifies more than 9 times the true number. While RL3 and OrpheusDB significantly improve upon Vanilla Git and Optimized Git false positive rate, the improvement comes at an unacceptable cost, as upwards of 75% of non-auto-mergeable records may be falsely flagged as auto-mergeable. In general, accuracy in identifying conflicts is independent of any underlying implementation details.

Figure 4 also benchmarks both the time needed to commit a set of modifications and any tracking metadata, as well as the time needed to analyze the committed data to find conflicts. The significant overhead with both recording and shipping data diffs is reflected in the increased commit times. Note that the commit times for the logical tracking methods are negligible, since only histories, at most a few kilobytes, need to be shipped. Figure 4 demonstrates that analyzing data diffs for conflicts is significantly more intensive than logical approaches like MindPalace and virtual locking, whose largest overhead is querying the original version. For the git-based methods, the extra overhead in the analysis step is largely due to the textual processing of the git diff output (which is at least as large as a textual dump of the database). For OrpheusDB, we believe the extra overhead is due to the view materialization needed to execute a three-way JOIN query on its versioning metadata to extract conflicting records.

7.5 Scalability of MindPalace

The ground-truth algorithm, even with optimizations, simply becomes infeasible at these scales in terms of running time. In contrast, MindPalace not only scales well but also has roughly the same accuracy as size increases. We vary larger data sizes from 10 GB to 100 GB, and demonstrate that performance times remain practical. In each trial, we report the average running time of a size 15 history with UPDATES/INSERTS/DELETES ratio = 75/20/5 and simple/complex predicates ratio = 80/20. We illustrate the results in Figure 5, maintaining the rest of the default data parameters.

7.6 Version Reconciliation

We measure the performance of version reconciliation. We consider different history sizes ranging from 10 to 100, and probabilities of conflicting ranging from 0.01% to 20% for each pair of modifications (a workflow with higher query selectivities may not be fit for a DVDS). For each parameter set, we generate 100k different randomly generated partial orders as the user’s desired interleaving, simulate our user interaction framework, and report the average number of questions asked by MindPalace in Figure 6. The figure shows that the number of question asked increase as the size of history and/or the probability of conflict increase, but the absolute number remains low. For example, when
the size of histories is 100 and conflict probability is 1%, MindPalace asks less than 5 questions on average (note that in this case, the expected number of conflicting modification pairs is $100 \times 100 \times 1% = 100$). This not only verifies our theoretical analysis that the number of user-interactions is bounded by the (sum of) sizes of the two histories, but also demonstrates the efficiency of our version reconciliation framework.

8 CONCLUSION

We present MindPalace, a lightweight method for version reconciliation in distributed versioned database systems. MindPalace identifies when disconnected histories of operations can safely merge together, and if not identifies the records and conflicting operations that need to be manually reconciled. We believe MindPalace is a critical component for building disconnected collaborative data systems, and opens up interesting subsequent research questions.

REFERENCES

[1] Farhana Aleen and Nathan Clark. 2009. Commutativity Analysis for Software Parallelization: Letting Program Transformations See the Big Picture. In Proceedings of the 14th International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS XIV). ACM, New York, NY, USA, 241–252. https://doi.org/10.1145/1508244.1508273

[2] Peter Alvaro, Neil Conway, Joseph M. Hellerstein, and David Maier. 2017. Blazes: Coordination Analysis and Placement for Distributed Programs. ACM Trans. Database Syst. 42, 4, Article 23 (Oct. 2017), 31 pages. https://doi.org/10.1145/3101214

[3] Peter Alvaro, Neil Conway, Joseph M. Hellerstein, and William R. Marczak. 2011. Consistency Analysis in Bloom: a CALM and Collected Approach. In CIDR 2011, Fifth Biennial Conference on Innovative Data Systems Research, Asilomar, CA, USA, January 9-12, 2011, Online Proceedings. www.cidrdb.org, Asilomar, California, 249–260. http://cidrdb.org/cidr2011/Papers/CIDR11_Paper35.pdf

[4] Attic Labs. 2021. noms. https://github.com/attic-labs/noms.

[5] Peter Bailis. 2015. Coordination Avoidance in Distributed Databases. Ph.D. Dissertation. University of California, Berkeley, USA. http://www.escholarship.org/uc/item/8k359g2

[6] Peter Bailis, Alan Fekete, Michael J. Franklin, Ali Ghodsi, Joseph M. Hellerstein, and Ion Stoica. 2014. Coordination Avoidance in Database Systems. Proc. VLDB Endow. 8, 3 (Nov. 2014), 185–196. https://doi.org/10.14778/2735508.2735509

[7] Valter Balegas, Sérgio Duarte, Carla Ferreira, Rodrigo Rodrigues, and Nuno Preguiça. 2018. IPA: Invariant-preserving Applications for Weakly Consistent Replicated Databases. Proc. VLDB Endow. 12, 4 (Dec. 2018), 404–416. https://doi.org/10.14778/3297753.3297760

[8] A. J. Bernstein, P. M. Lewis, and S. Lu. 2000. Semantic conditions for correctness at different isolation levels. In Proceedings of 16th International Conference on Data Engineering (Cat. No.00CB37073). IEEE Computer Society, Washington, DC, USA, 57–66. https://doi.org/10.1109/ICDE.2000.839387

[9] Philip A. Bernstein, Alan Fekete, Hongfei Guo, Raghu Ramakrishnan, and Pradeep Tamma. 2006. Relaxed-currency Serializability for Middle-tier Caching and Replication. In Proceedings of the 2006 ACM SIGMOD International Conference on Management of Data (Chicago, IL, USA) (SIGMOD ’06). ACM, New York, NY, USA, 599–610. https://doi.org/10.1145/1142473.1142540

[10] Anant P. Bhardwaj, Souvik Bhattacharjee, Amit Chavan, Amol Deshpande, Aaron J. Elmore, Samuel Madden, and Aditya G. Parameswaran. 2015. DataHub: Collaborative Data Science & Dataset Version Management at Scale. In CIDR 2015, Seventh Biennial Conference on Innovative Data Systems Research, Asilomar, CA, USA, January 4-7, 2015, Online Proceedings. www.cidrdb.org. http://cidrdb.org/cidr2015/Papers/CIDR15_Paper18.pdf

[11] Lucas Brutschy, Dimitar Dimitrov, Peter Müller, and Martin Vechev. 2017. Serializability for Eventual Consistency: Criteria, Analysis, and Applications. In Proceedings of the 44th ACM SIGPLAN Symposium on Principles of Programming Languages (Paris, France) (POPL ’17). ACM, New York, NY, USA, 458–472. https://doi.org/10.1145/3009837.3009895

[12] Sebastian Burckhardt, Alexandre Baldassin, and Daan Leijen. 2010. Concurrent Programming with Revisions and Isolation Types. In Proceedings of the ACM International Conference on Object Oriented Programming Systems Languages and Applications (Reno/Tahoe, Nevada, USA) (OOPSLA ’10). ACM, New York, NY, USA, 691–707. https://doi.org/10.1145/1869459.1869615

[13] Sebastian Burckhardt, Alexey Gotsman, Hongseok Yang, and Marek Zawirski. 2014. Replicated Data Types: Specification, Verification, Optimality. In Proceedings of the 41st ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (San Diego, California, USA) (POPL ’14). ACM, New York, NY, USA, 271–284. https://doi.org/10.1145/2535838.2535848

[14] Prima Chairunnanda, Khuzaima Daudjee, and M. Tamer Ozsu. 2014. ConfluxDB: Multi-master Replication for Partitioned Snapshot Isolation Databases. Proc. VLDB Endow. 7, 11 (July 2014), 947–958. https://doi.org/10.14778/2732967.2732970

[15] Austin T. Clements, M. Frans Kaashoek, Nickolai Zeldovich, Robert T. Morris, and Eddie Kohler. 2015. The Scalable Commutativity Rule: Designing Scalable Software for Multicore Processors. ACM Trans. Comput. Syst. 32, 4, Article 10 (Jan. 2015), 47 pages. https://doi.org/10.1145/2699681

[16] Natacha Crooks, Youer Ps, Lorenzo Alvisi, and Allen Clement. 2017. Seeing is Believing: A Client-Centric Specification of Database Isolation. In Proceedings of the ACM Symposium on Principles of Distributed Computing (Washington, DC, USA) (PODC ’17). Association for Computing Machinery, New York, NY, USA, 73–82. https://doi.org/10.1145/3087801.3087802

[17] Natacha Crooks, Youer Ps, Nancy Estrada, Trinabh Gupta, Lorenzo Alvisi, and Allen Clement. 2016. TARDIS: A Branch-and-Merge Approach To Weak Consistency. In Proceedings of the 2016 International Conference on Management of Data (San Francisco, California, USA) (SIGMOD ’16). ACM, New York, NY, USA, 1615–1628. https://doi.org/10.1145/2882903.2882951

[18] Databricks. [n.d.]. Introduction to Delta Lake. https://docs.databricks.com/delta/delta-intro.html?_ga=2.85364377.1242105.1582418006-552522563.1582418006.2020-09-22.

[19] DoltHub, Inc. 2021. Dolt. https://www.dolthub.com/.

[20] Paul Fitzpatrick. 2021. daff. https://paulfitz.github.io/daff/.

[21] Alexey Gotsman, Hongseok Yang, Carla Ferreira, Mahsa Najafzadeh, and Marc Shapiro. 2016. ‘Cause I’m Strong Enough: Reasoning About Consistency Choices in Distributed Systems. In Proceedings of the 43rd Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages (St. Petersburg, FL, USA) (POPL ’16). ACM, New York, NY, USA, 371–384. https://doi.org/10.1145/2837614.2837625

[22] Vincent Gramoli and Rachid Guerraoui. 2014. Democratizing Transactional Programming. Commun. ACM 57, 1 (Jan. 2014), 86–93. https://doi.org/10.1145/2541883.2541900
[23] Hongfei Guo, Per-Ake Larson, and Raghu Ramakrishnan. 2005. Caching with “Good Enough” Currency. Consistency, and Completeness. In Proceedings of the 31st International Conference on Very Large Data Bases (VLDB ’05). VLDB Endowment, Trondheim, Norway, 457–468. http://dl.acm.org/citation.cfm?id=1083592.1083647

[24] Hongfei Guo, Per-Ake Larson, Raghu Ramakrishnan, and Jonathan Goldstein. 2004. Relaxed Currency and Consistency: How to Say “Good Enough” in SQL. In Proceedings of the 2004 ACM SIGMOD International Conference on Management of Data (Paris, France) (SIGMOD ’04). ACM, New York, NY, USA, 815–826. https://doi.org/10.1145/1007568.1007661

[25] Hongfei Guo, Per-Ake Larson, Raghu Ramakrishnan, and Jonathan Goldstein. 2004. Support for Relaxed Currency and Consistency Constraints in MTCache. In Proceedings of the 2004 ACM SIGMOD International Conference on Management of Data (Paris, France) (SIGMOD ’04). ACM, New York, NY, USA, 937–938. https://doi.org/10.1145/1007568.1007706

[26] Joseph M. Hellerstein. 2010. The Declarative Imperative: Experiences and Conjectures in Distributed Logic. SIGMOD Rec. 39, 1 (Sept. 2010), 5–19. https://doi.org/10.1145/1860702.1860704

[27] Maurice Herlihy and Eric Koskinen. 2008. Transactional Boosting: A Methodology for Highly-concurrent Transactional Objects. In Proceedings of the 13th ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming (Salt Lake City, UT, USA) (PPoPP ’08). ACM, New York, NY, USA, 207–216. https://doi.org/10.1145/1345206.1345237

[28] Silu Huang, Liqi Xu, Jialin Liu, Aaron J Elmore, and Aditya Parameswaran. 2017. Orpheus DB: bolt-on versioning for relational databases. Proceedings of the VLDB Endowment 10, 10 (2017), 1130–1141.

[29] Iterative, Inc. 2021. Dava Version Control. https://dvc.org/.

[30] J. R. Jordan, J. Banerjee, and R. B. 1981. Precision Locks. In Proceedings of the 1981 ACM SIGMOD International Conference on Management of Data (Ann Arbor, Michigan) (SIGMOD ’81). Association for Computing Machinery, New York, NY, USA, 143–147. https://doi.org/10.1145/582318.582340

[31] Tim Kraska, Martin Hentschel, Gustavo Alonso, and Donald Kossmann. 2009. Consistency Rationing in the Cloud: Pay Only when It Matters. Proc. VLDB Endow. 2, 1 (Aug. 2009), 253–264. https://doi.org/10.14778/1687627.1687657

[32] Milind Kulkarni, Donald Nguyen, Dimitrios Prountzos, Xin Sui, and Keshav Pingali. 2011. Exploiting the Commutativity Latice. In Proceedings of the 32Nd ACM SIGPLAN Conference on Programming Language Design and Implementation (San Jose, California, USA) (PLDI ’11). ACM, New York, NY, USA, 542–555. https://doi.org/10.1145/1993498.1993562

[33] P. Ake. Larson, J. Goldstein, and J. Zhou. 2004. MTCache: transparent mid-tier database caching in SQL server. In Proceedings. 20th International Conference on Data Engineering, IEEE Computer Society, Washington, DC, USA, 177–188. https://doi.org/10.1109/ICDE.2004.1319994

[34] Cheng Li, João Leitão, Allen Clement, Nuno Preguiça, Rodrigo Rodrigues, and Viktor Vafeiadis. 2014. Automating the Choice of Consistency Levels in Replicated Systems. In Proceedings of the 2014 USENIX Conference on USENIX Annual Technical Conference (Philadelphia, PA) (USENIX ATC’14). USENIX Association, Berkeley, CA, USA, 281–292. http://dl.acm.org/citation.cfm?id=2643634.2643664

[35] Cheng Li, Daniel Porto, Allen Clement, Johannes Gehrke, Nuno Preguiça, and Rodrigo Rodrigues. 2012. Making Geo-replicated Systems Fast As Possible, Consistent when Necessary. In Proceedings of the 10th USENIX Conference on Operating Systems Design and Implementation (Hollywood, CA, USA) (OSDI’12). USENIX Association, Berkeley, CA, USA, 265–278. http://dl.acm.org/citation.cfm?id=2387880.2387906

[36] Cheng Li, Nuno Preguiça, and Rodrigo Rodrigues. 2018. Fine-grained consistency for geo-replicated systems. In 2018 USENIX Annual Technical Conference (USENIX ATC’18). USENIX Association, Boston, MA, 359–372. https://www.usenix.org/conference/ate18/presentation/li-cheng

[37] Michael Maddox, David Goehring, Aaron J Elmore, Samuel Madden, Aditya Paremswaran, and Amol Deshpande. 2016. Decibel: The relational dataset branching system. Proceedings of the VLDB Endowment 9, 9 (2016), 624–635.

[38] Neha Narula, Cody Cutler, Eddie Kohler, and Robert Morris. 2014. Phase Reconciliation for Contended In-memory transactions. In Proceedings of the 11th USENIX Conference on Operating Systems Design and Implementation (Broomfield, CO) (OSD’14). USENIX Association, Berkeley, CA, USA, 511–524. http://dl.acm.org/citation.cfm?id=2685048.2685088

[39] Chris Olston, Boon Thau Loo, and Jennifer Widom. 2001. Adaptive Precision Setting for Cached Approximate Values. In Proceedings of the 2001 ACM SIGMOD International Conference on Management of Data (Santa Barbara, California, USA) (SIGMOD ’01). ACM, New York, NY, USA, 355–366. https://doi.org/10.1145/375663.375710

[40] Chris Olston and Jennifer Widom. 2000. Offering a Precision-Performance Tradeoff for Aggregation Queries over Replicated Data. In Proceedings of the 26th International Conference on Very Large Data Bases (VLDB ’00). Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 144–155. http://dl.acm.org/citation.cfm?id=645926.671877

[41] Pachyderm Inc. 2021. Pachyderm. https://www.pachyderm.com/.

[42] Calton Pu. 1992. Relaxing the Limitations of Serializable Transactions in Distributed Systems. In Proceedings of the 5th Workshop on ACM SIGOPS European Workshop: Models and Paradigms for Distributed Systems Structuring (Mont Saint-Michel, France) (EW-5). ACM, New York, NY, USA, 1–6. https://doi.org/10.1145/506378.506415

[43] Martin C. Rinard and Pedro C. Diniz. 1997. Commutativity Analysis: A New Analysis Technique for Parallelizing Compilers. ACM Trans. Program. Lang. Syst. 19, 6 (Nov. 1997), 942–991. https://doi.org/10.1145/267939.269969

[44] Martin C. Rinard and Pedro C. Diniz. 1997. Commutativity Analysis: A New Analysis Technique for Parallelizing Compilers. ACM Trans. Program. Lang. Syst. 19, 6 (Nov. 1997), 942–991. https://doi.org/10.1145/267939.269969

[45] Zechao Shang, Jeffrey Xu Yu. 2017. My Weak Consistency is Strong. In CIDR 2017, 8th Biennial Conference on Innovative Data Systems Research, Chaminade, CA, USA, January 8-11, 2017, Online Proceedings. www.cidrdb.org. http://cidrdb.org/cidr2017/papers/p115-shang-cidr17.pdf

[46] Zechao Shang, and Jeffrey Xu Yu. 2017. My Weak Consistency is Strong. In CIDR 2017, 8th Biennial Conference on Innovative Data Systems Research, Chaminade, CA, USA, January 8-11, 2017, Online Proceedings. www.cidrdb.org. http://cidrdb.org/cidr2017/papers/p115-shang-cidr17.pdf

[47] Dennis Shasha, Eric Simon, and Patrick Valduriez. 1992. Simple Ratio-
[49] Douglas B. Terry, Marvin M. Theimer, Karin Petersen, Alan J. Demers, Mike J. Spreitzer, and Carl H. Hauser. 1995. Managing update conflicts in Bayou, a weakly connected replicated storage system. ACM SIGOPS Operating Systems Review 29, 5 (1995), 172–182.

[50] Omer Tripp, Roman Manevich, John Field, and Mooly Sagiv. 2012. JANUS: Exploiting Parallelism via Hindsight. In Proceedings of the 33rd ACM SIGPLAN Conference on Programming Language Design and Implementation (Beijing, China) (PLDI ’12). ACM, New York, NY, USA, 145–156. https://doi.org/10.1145/2254064.2254083

[51] Todd L. Veldhuizen. 2014. Transaction Repair: Full Serializability Without Locks. CoRR abs/1403.5645 (2014). arXiv:1403.5645 http://arxiv.org/abs/1403.5645

[52] Tobias J. K. Edler von Koch, Stanislav Manilov, Christos Vasilakidis, Murray Cole, and Björn Franke. 2018. Towards a Compiler Analysis for Parallel Algorithmic Skeletons. In Proceedings of the 27th International Conference on Compiler Construction (Vienna, Austria) (CC 2018). ACM, New York, NY, USA, 174–184. https://doi.org/10.1145/3178372.3179513

[53] Sheng Wang, Tien Tuan Anh Dinh, Qian Lin, Zhongle Xie, Meihui Zhang, Qingchao Cai, Gang Chen, Beng Chin Ooi, and Pingcheng Ruan. 2018. Forkbase: An efficient storage engine for blockchain and forkable applications. Proceedings of the VLDB Endowment 11, 10 (2018), 1137–1150.

[54] Zhaoguo Wang, Shuai Mu, Yang Cui, Han Yi, Haibo Chen, and Jinyang Li. 2016. Scaling Multicore Databases via Constrained Parallel Execution. In Proceedings of the 2016 International Conference on Management of Data (San Francisco, California, USA) (SIGMOD ’16). ACM, New York, NY, USA, 1643–1658. https://doi.org/10.1145/2882903.2882934

[55] W. E. Weihl. 1988. Commutativity-based concurrency control for abstract data types. IEEE Trans. Comput. 37, 12 (Dec 1988), 1488–1505. https://doi.org/10.1109/12.9728

[56] W. E. Weihl. 1989. Local Atomicity Properties: Modular Concurrency Control for Abstract Data Types. ACM Trans. Program. Lang. Syst. 11, 2 (April 1989), 249–282. https://doi.org/10.1145/65264.65218

[57] Michael Whittaker and Joseph M. Hellerstein. 2018. Interactive Checks for Coordination Avoidance. Proc. VLDB Endow. 12, 1 (Sept. 2018), 14–27. https://doi.org/10.14778/3275536.3275538

[58] Kun-Lung Wu, Philip S. Yu, and Calton Pu. 1992. Divergence Control for Epsilon-Serializability. In Proceedings of the Eighth International Conference on Data Engineering. IEEE Computer Society, Washington, DC, USA, 506–515. http://dl.acm.org/citation.cfm?id=645477.654631

[59] Kun-Lung Wu, Philip S. Yu, and Calton Pu. 1997. Divergence Control Algorithms for Epsilon Serializability. IEEE Trans. on Knowl. and Data Eng. 9, 2 (March 1997), 262–274. https://doi.org/10.1109/69.591451

[60] Yingjun Wu, Chee-Yong Chan, and Kian-Lee Tan. 2016. Transaction Healing: Scaling Optimistic Concurrency Control on Multicores. In Proceedings of the 2016 International Conference on Management of Data (San Francisco, California, USA) (SIGMOD ’16). ACM, New York, NY, USA, 1689–1704. https://doi.org/10.1145/2882903.2915202

[61] Chao Xie, Chunzhi Su, Cody Littley, Lorenzo Alvisi, Manos Kapritsos, and Yang Wang. 2015. High-performance ACID via Modular Concurrency Control. In Proceedings of the 25th Symposium on Operating Systems Principles (Monterey, California) (SOSP ’15). ACM, New York, NY, USA, 279–294. https://doi.org/10.1145/2815400.2815430

[62] K. Zellag and B. Kemme. 2011. Real-time quantification and classification of consistency anomalies in multi-tier architectures. In 2011 IEEE 27th International Conference on Data Engineering. IEEE Computer Society, Washington, DC, USA, 613–624. https://doi.org/10.1109/ICDE.2011.5767927

[63] Kamal Zellag and Bettina Kemme. 2012. How Consistent is Your Cloud Application?. In Proceedings of the Third ACM Symposium on Cloud Computing (San Jose, California) (SoCC ’12). ACM, New York, NY, USA, Article 6, 14 pages. https://doi.org/10.1145/2391229.2391235

[64] Kamal Zellag and Bettina Kemme. 2014. Consistency Anomalies in Multi-tier Architectures: Automatic Detection and Prevention. The VLDB Journal 23, 1 (Feb. 2014), 147–172. https://doi.org/10.1007/s00778-013-0518-x

[65] Yang Zhang, Russell Power, Siyuan Zhou, Yair Sovran, Marcos K. Aguilera, and Jinyang Li. 2013. Transaction Chains: Achieving Serializability with Low Latency in Geo-distributed Storage Systems. In Proceedings of the Twenty-Fourth ACM Symposium on Operating Systems Principles (Farmington, Pennsylvania) (SOSP ’13). ACM, New York, NY, USA, 276–291. https://doi.org/10.1145/2517349.2522729