Validating Database System Isolation Level Implementations with Version Certificate Recovery

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Abstract

Transactions are a key feature of database systems and isolation levels specify the behavior of concurrently executing transactions. Ensuring their correct behavior is crucial. Recently, many isolation anomalies have been found in production database systems. Checkers can be used to validate that a particular execution conforms to a desired isolation level. However, state-of-the-art checkers cannot handle predicate operations, which are both common in real-world workloads and essential for distinguishing between the *repeatable read* and *serializable* isolation levels. In this work, we address this issue by proposing an efficient white-box checker, Emme. Our key idea is to use information that is easily provided by database systems to efficiently check the isolation level of a given transaction history. We present *version certificate recovery*, a method of recovering the *version order* and each operation's *version* from the database system under test. For efficiency, we also propose the concept of an *expected serialization order*, which obviates the need to define and recover a version certificate for many *serializable* concurrency control protocols. We have implemented version certificate recovery for three widely used database systems—PostgreSQL, CockroachDB, and TiDB. We demonstrate that Emme is 1.2–3.6× faster than Elle, a state-of-the-art checker. Using the expected serialization order, we obtain a further speedup of 34–430× compared to Emme when checking histories containing predicate operations. We show that our approach can identify invalid histories that cannot be detected by Elle and also show that it can find realistic bugs purposely introduced by an engineer.

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1 Introduction

A core feature of many database systems is grouping operations into *transactions* [16]. The extent to which operations within a transaction interact with operations from other concurrent transactions is defined by an *isolation level*. Database systems offer a range of isolation levels [2, 3, 5, 7, 13], with each level providing different guarantees to client applications. The guarantees that an isolation level offers are typically defined in terms of *anomalies* that any possible *execution history*—a record of the operations submitted to and the results received from the database system—must not contain [3, 5, 7]. It is vital that database systems provide the isolation guarantees that they claim, because bugs leading to weaker guarantees can corrupt application state [24] and cause significant security vulnerabilities [48].

Automated testing approaches have found a wide variety of bugs in the implementation of various database systems' isolation levels [22]. This includes bugs in widely used and stable systems such as PostgreSQL [35], which had a bug in the implementation of its *serializable* isolation level [34]. Despite the success of these approaches, it would be desirable to obtain more confidence that isolation-level guarantees are met. Formal verification approaches for mature database systems and their isolation levels are still out of reach [27]. In contrast, so-called *checkers* [4, 10, 45] enable validating that *a particular execution history* conforms to the isolation level that the database system claims to support. In other words, such checkers enable approaching the problem through a *translation validation* [29, 32] lens, allowing clients to verify that the operations performed by the database system conform to the desired isolation level. However, these checkers suffer from at least one of two major problems.

Problem 1: high run-time overhead. For important isolation levels such as *serializability* and *snapshot isolation*,

$$T_1 : w_1(x, 1)$$
$$T_2 : w_2(y, 2)$$
$$T_3 : r_3(< 5, \{x\}),\ r_3(< 5, \{x,\ y\})$$

Figure 1. This non-serializable history has three committed transactions. T_3 contains a phantom read. It issues two identical predicate operations that read all objects in the database whose value is less than five. The first operation returns the object x, but the second one returns both x and y.

checking whether a history is valid is an NP-complete problem [9, 10, 31]. Efficiently supporting large and highly concurrent histories is important because many randomized testing approaches rely on executing large numbers of transactions from many clients. Checkers in prior work either use workload-specific optimizations to improve the size of histories they support [45] or scale poorly as the concurrency in the history increases [10]. The exception, Elle [4], a checker for histories produced by the Jepsen testing framework [21], relies on an encoding scheme that works efficiently only if all writes in the history are atomic list-append operations; a requirement that some database systems (e.g., TiKV [46]) cannot fulfill. Furthermore, even in systems that *do* support atomic list-append operations, there is no guarantee that exclusive use of these operations can catch bugs in the implementation of other operations.

Problem 2: lack of support for predicate operations. Predicate operations, such as the SQL statement `SELECT * FROM t0 WHERE c0 > 7`, return all rows that satisfy a given predicate (`c0 > 7` in this case). They are widely used in most database systems, enabling more complex features such as scans, joins, and aggregates. These features typically require additional implementation complexity and potentially more complex concurrency control mechanisms such as predicate locking [16]. Predicate operations can cause unique types of anomalies in histories, known as *predicate anomalies*, that simple key-value reads and writes cannot cause. For example, the history shown in Fig. 1 contains a *phantom read* anomaly [16]. These unique predicate anomalies have been observed in production database systems [28]. In fact, predicate anomalies are the sole means by which the industry-standard Adya model [3] distinguishes between *serializability* and the weaker *repeatable read* isolation level. Therefore the inability of current checkers to detect predicate anomalies is a severe limitation: they cannot distinguish between these isolation levels for histories containing predicate operations.

Our contributions. We address these problems through a white-box checking approach. Although our checker is white-box, we show that after a small amount of initial work from someone familiar with the database system, the information needed by the checker can be exposed via a black-box API. This enables clients to use the checker in a fully black-box manner. This is particularly valuable in a cloud setting where vendors may not want to reveal proprietary implementation details. Our checker has the following unique features:

1. It supports efficient checking of large and highly concurrent histories by recovering a version certificate from the database system via a simple interface, without requiring support for atomic list-append operations (or any other particular operation).
2. It is the first checker capable of supporting histories containing predicate operations. As a result, it is the only checker able to check the *serializability* of histories resulting from common database workloads.

Our core insight is that it is possible to use the invariant(s) that guarantee the correctness of a database system's concurrency control protocol to define and recover a so-called *version certificate*. A version certificate consists of an *expected version order* and, for every predicate operation in the history, an *expected version set*. Roughly, the expected version order is a per-object total order on writes to the database, while the expected version set of a predicate operation is the set of values over which it will evaluate its predicate. A checker based on the Adya model [3] of isolation levels can then use the version certificate to certify that the corresponding execution history conforms to a given isolation level or reject it.

- The checker will accept a history as valid if the expected version order and expected version sets form a valid version certificate to show that the history meets the requirements of the desired isolation level. Since the certificate was derived from the invariants that guarantee the correctness of the concurrency control protocol, we provide stronger guarantees than existing checkers: our checker will confirm a history as valid only if the history meets the desired isolation level *by design*. A history that meets the desired isolation coincidentally—despite violating these invariants—will be flagged as invalid, uncovering defects in the implementation of the protocol that would otherwise go unnoticed.
- The checker will reject the history as invalid if the version certificate cannot be used to show that the desired isolation level has been met. In this case, there *might* nevertheless exist *some* version certificate that could be used to validate the history. However, the fact that the certificate did not lead to confirmation that the required isolation level had been met implies that either (a) the invariants of the concurrency control protocol were violated during execution or (b) the invariants were insufficiently strong to provide the required isolation level. Both of these cases indicate errors in the database system. Therefore, from the point of view of a database developer, we argue that it is irrelevant that the history could be certified using some

other certificate and it is *valuable* that the checker can demonstrate these defects by rejecting the history.

A benefit of our core approach is that it is very general: it works for a wide range of isolation levels and database systems due to the central role that both the version order and version sets play in defining isolation levels in the widely used Adya model. As an additional contribution, we present a more specialized approach that is even more effective for many *serializable* concurrency control protocols. This approach defines an *expected serialization order*—a total order on committed transactions such that they must be *serializable* in that order—that can be used to certify a history. This approach avoids the need to define and recover a version certificate and allows significantly faster checking, particularly for histories containing predicate operations.

We have implemented the version certificate recovery interface for three diverse and widely used systems: PostgreSQL [35], CockroachDB [44], and TiDB [20]. We have also implemented a practical checker, Emme, which supports *serializability* and *snapshot isolation*. Despite the distinct concurrency control protocols used by these systems, we show that it takes no more than a few hundred lines of Python code to implement the interface for each system. To demonstrate the effectiveness of version certificate recovery, we show that it can detect a faulty history caused by a known bug in an old version of PostgreSQL's *serializable* isolation level. Additionally, Cockroach Labs supported our work by introducing three bugs of their own choosing into a fork of CockroachDB that affect its *serializability* guarantees. We demonstrate that version certificate recovery expectedly rejects invalid histories caused by all three bugs. We also show that our approach can detect predicate-only anomalies in histories produced by running PostgreSQL at the *read committed* isolation level, and that Elle—a state-of-the-art checker—is unable to detect these anomalies and will incorrectly validate these histories as *serializable*.

We compare the checking performance of Emme against Elle and find that for histories without predicate operations, Emme has up to 4× better performance. For histories containing predicate operations, we demonstrate that Emme can check histories of 2500 transactions in under two minutes, making Emme the first checker able to support predicate operations for non-trivial histories. Finally, we show that the more specialised expected serialization order technique significantly outperforms both Elle and Emme, with a speedup ranging from 34x to 430x compared to Emme on non-predicate histories, and a speedup ranging from 53x to 120x for predicate histories. Furthermore, we show that the expected serialization order technique scales significantly better than Emme for histories containing predicate operations allowing much larger histories to be supported.

2 Example-Driven Overview

Our approach consists of version certificate recovery—the technique for recovering sufficient information from the database system to enable efficient checking—and our checker, Emme. We imagine a scenario where a proprietary cloud database company has tasked an engineer with a) ensuring that their system correctly implements its isolation level guarantees and b) providing clients with a means of validating these guarantees.

To this end, the engineer can use our approach based on three steps: (1) defining the expected version order and expected version sets that will form the version certificate, (2) implementing mechanisms to retrieve any information from the database system that is necessary to recover the expected version order and version sets, and (3) implementing the black-box API that outputs the version certificate. Finally, for validation, both the engineer and client can retrieve the version certificate from the black-box API and input it along with the recorded execution history into our checker to verify that the history complies with the required isolation level.

Let us assume the database system uses a multiversion concurrency control timestamp ordering protocol (MVTO) to guarantee *serializability* [38]. In such a protocol, each transaction is assigned a unique timestamp which is associated with all of its operations. Additionally, each version of an object is assigned the timestamp of the transaction that created it. The correctness of the protocol depends on the invariant that ordering the operations of committed transactions in ascending timestamp order will produce an equivalent serial history that is *serializable*. It follows that choosing a version order consistent with timestamp order will guarantee a *serializable* history in any correct execution. A further implication of the timestamp order invariant is that it must always be possible for a transaction to execute its operations using the version of each object with the greatest timestamp that is less than or equal to its own. These facts should already be clear to a developer implementing the protocol, however, if a different developer is deriving the version certificate, then they can discover these facts by consulting a standard textbook describing MVTO [9].

With the knowledge above, it is clear that the expected version order should be defined as the total order resulting from sorting versions in ascending timestamp order (where versions written by the same transaction appear in transaction order). Each operation's expected version set can be defined to contain the version of each object with the greatest timestamp that is less than the predicate operation's timestamp, or if the operation's transaction has modified an object, the latest version of the object modified by the transaction.

To recover the expected version order and version sets for any particular execution history, the engineer needs to recover the timestamps associated with each transaction (and

$$T_1 : w_1(x, 1)$$
$$T_2 : w_2(y, 2)$$
$$T_3 : r_3(> 0, \{x, y\})$$

Figure 2. A history that is *serializable* in ascending timestamp order. Transaction identifiers act as timestamps.

$$T_1 : w_1(x, 1)$$
$$T_2 : w_2(y, 2)$$
$$T_3 : r_3(> 0, \{x\})$$

Figure 3. A history for which ordering transactions by their timestamps ($T_1 \rightarrow T_2 \rightarrow T_3$) does not produce a *serializable* order. There is another order ($T_1 \rightarrow T_3 \rightarrow T_2$) that is *serializable*, however, it contradicts the timestamp order. Transaction identifiers act as timestamps.

therefore each operation). In our experience, most timestamp-ordering database systems include this in the transaction metadata. Therefore, the engineer can use this metadata to automatically recover the timestamp associated with each transaction, generate the version certificate, and make it available via a black-box API. This is the last step that requires any knowledge of the database system internals.

Finally, the engineer or client can recover the version certificate via the black-box API and provide it as input along with the history to Emme, which will use the certificate to check that the history is *serializable*. Fig. 2 contains a history that Emme will verify as *serializable* using the trivial version order that arises from a single write to each object in a history, and the expected version set $\{x, y\}$ for r_3. In the examples within this section, the transaction identifiers are also their timestamps, for example, T_1 has timestamp 1. Since both the version order and version set have been derived from the timestamp order, we can be sure that the history is not only *serializable*, but respects the key timestamp ordering invariant of the MVTO protocol.

Fig. 3 demonstrates a history that does not form a *serializable* serial order when arranged in timestamp order. The expected version set of r_3 is $\{x, y\}$, however, r_3 only reads x despite y also matching the predicate condition *(> 0)*. Clearly, this should never happen in a database system using the MVTO protocol. However, black-box checkers will verify this history as *serializable* using the serial order $T_1 \rightarrow T_3 \rightarrow T_2$, despite the fact that this violates the timestamp order invariant, as they have no knowledge of the underlying protocol used. In contrast, Emme will reject this history as it recognizes that the invariant used to derive the version certificate has been broken, indicating either an implementation error in the database system, or the use of an incorrect invariant. This is a valuable feature of our checker, as it can detect defects in concurrency control protocols that would otherwise be missed by black-box checkers.

It is also possible to derive an expected serialization order for the MVTO protocol. An expected serialization order is a total ordering of transactions such that they must be *serializable* in that order. For the MVTO protocol, this is simply ascending timestamp order. There are many benefits to using the expected serialization order approach compared to generating a version certificate. Firstly, an engineer only needs to derive an expected serialization order, rather than both an expected version order and the expected version sets, which is typically much easier. Secondly, there is no need to implement version certificate recovery for the database system. Finally, as demonstrated in Section 7, the checking performance and scalability of Emme are vastly improved when using an expected serialization order, particularly for histories containing many predicate operations.

We highlight, both through this MVTO example and the examples in Section 5, that the invariants required by our approach are high level and can be derived from the proof of correctness or formal specification of a protocol. This is particularly useful for distributed database systems, where it is becoming more common to formally specify the invariants of a concurrency control protocol in a language such as TLA$^+$ [25]. Furthermore, the invariants do not require analysis of the database system code and are robust to changes in implementation details that do not affect the correctness proof of the protocol.

3 Adya Model

Our checker uses the isolation level model introduced by Adya et al. [3], so this section provides an overview of the model to aid in understanding how our checker works, and also demonstrates the theoretical basis for checking histories containing predicate operations.

An Adya history H comprises a set of operations performed by transactions and a version order ($\ll$). The database consists of a set of abstract objects and operations act on a particular version of each object. Write operations introduce a new version of an object and read operations read a particular version of an object. The version order ($\ll$) is defined as a per-object total order over committed versions. $x_i \ll x_j$ means that x_i appears before x_j in the version order.

The Adya model also defines predicate operations, which operate on versions matching a particular predicate condition P. Since many versions of a particular object may exist, the database system conceptually chooses a single version of each object over which to evaluate the predicate. This is called the version set, $Vset(P)$, of the predicate operation.

Isolation levels are defined within the Adya model by the different types of *anomalies* that are allowed to occur. The Adya model defines two non-cyclic anomalies, *aborted reads* and *intermediate reads* that are disallowed in every isolation level other than the *read uncommitted* (PL-1) isolation level.

$T_1: \ w_1(x_1 = 4)$
$T_2: \ w_2(x_2 = 6)$
$T_3: \ r_3(< 5 : x_2)\ \{\},\ r_3(x_1 = 4)$
Version Order : $x_1 \ll x_2$

Figure 4. A non-serializable Adya history consisting of four operations. T_3 contains two operations—a predicate read that reads anything less than five, has x_2 in its version set, and an empty result set, followed by a normal read of x_1.

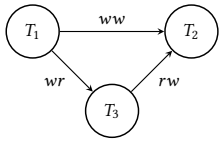

Figure 5. An item-DSG built from the history shown in Fig. 4.

In addition to the non-cyclic anomalies, there are also anomalies that are defined by the cycles that can occur in a *Direct Serialization Graph*.

Given an Adya history H, it is possible to build a *Direct Serialization Graph*, DSG(H). The nodes of the DSG(H) consist of the committed transactions in H and edges between transactions occur due to dependencies that arise from operations within the history. The Adya formalism introduces two types of dependencies—*item dependencies* and *predicate dependencies*. Three types of item dependencies exist (write-read, write-write, and read-write) that occur whenever a version of a single object is read or written. Let us call a DSG(H) that includes only the item dependencies in H the item-DSG(H). Fig. 5 shows the item-DSG that results from the Adya history in Fig. 4. The history contains three transactions, T_1, T_2 and T_3. Transactions T_1 and T_2 each write a new version of x. The third transaction, T_3, issues two operations—a predicate read operation and a read of x. The predicate read operation—$r_3(< 5 : x_2)\ \{\}$—tries to read any versions less than 5. It has a version set consisting of only x_2 and an empty result set (since x_2 is greater than 5).

An Adya history H is *serializable* if the resulting DSG(H) is acyclic when both item dependency edges and predicate dependency edges are considered. Notice that the history is not *serializable*, yet the item-DSG(H) is acyclic. Since the item-DSG(H) includes only item dependency edges, it is insufficient for checking *serializability*. Existing checkers that use the Adya model only build an item-DSG(H) and thus cannot check *serializability* as defined in the Adya model.

Predicate Dependencies. A central concept for defining predicate dependencies in the Adya model is the notion of *changing the matches* of a predicate operation. A version x_i changes the matches of a predicate operation $r_j(P\colon Vset(P))$ if x_i matches the predicate condition and the version x_h immediately preceding x_i in the version order does not match the condition or vice versa. Two types of predicate dependencies exist in the Adya model:

1. **A predicate read dependency (pred wr)**, which occurs from T_i to T_j when T_j issues a predicate read $r_j(P\colon Vset(P))$, $x_k \in Vset(P)$, $i = k$ or $x_i \ll x_k$, and x_i changes the matches of $r_j(P\colon Vset(P))$.
2. **A predicate anti-dependency (pred rw)**, which occurs from T_i to T_j when T_j overwrites a predicate read operation $r_i(P\colon Vset(P))$. T_j overwrites an operation $r_i(P\colon Vset(P))$ if T_j installs x_j such that x_k belongs to $Vset(P)$, $x_k \ll x_j$ and x_j changes the matches of $r_i(P\colon Vset(P))$.

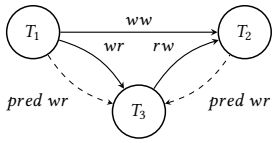

Figure 6. The DSG that is built when including predicate dependencies from the predicate operation $r_3(< 5 : x_2)\ \{\}$.

Recall the Adya history in Fig. 4. The corresponding DSG(H) is shown in Fig. 6 once predicate dependencies have been added. The predicate read dependency from T_2 to T_3 occurs because $w_2(x_2)$ is observed in the version set of the predicate read in T_3 and it would not match the predicate condition, whereas the previous version in the version order x_1 would have matched, therefore it changes the matches. This is the dependency that makes the graph cyclic and therefore violates *serializability*.

Imagine instead of x_2, x_1 was in the version set of the predicate operation in the history in Fig. 4. This results in the DSG shown in Fig. 7. This DSG is acyclic, despite the history not being *serializable*. This is because the Adya model assumes that if a version in the version set matches the predicate, it must be in the result set. However, this is not something a checker can assume, since the system may have an error. This requires us to add an additional anomaly to the Adya model, which we call a *result set mismatch*, which occurs when a version in the version set should have been included in the result set but was not or vice versa.

As well as predicate reads, the Adya model allows updates based on a predicate condition (*predicate updates*). Predicate updates are modelled as predicate reads followed by a sequence of item write operations that create a new version v_{new} for each version v_{old} that matched the predicate read. This captures common operations such as `UPDATE table SET c0 = 20, c1 = 20 WHERE c1 >= 0 AND c1 <= 10`.

4 Emme

We now describe our checker, Emme, which, given an Adya history and an isolation level, is responsible for determining if the history satisfies a given isolation level. Our checker supports multiple isolation levels, including *serializability*

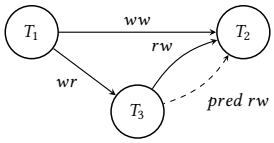

Figure 7. The DSG that is built when including predicate dependencies from the predicate operation $r_3(< 5 : x_1)$ {}.

Algorithm 1: The main checking function.

```
1  Def check(history, vo, isolation_spec):
2      txns = get_committed_txns(history)
3      deps = set()
4      for txn ∈ txns do
5          for op ∈ txn.ops do
6              item_deps = get_item_deps(op, vo)
7              pred_deps = get_pred_deps(op, vo)
8              deps = deps ∪ item_deps ∪ pred_deps
9      dsg = build_dsg(deps)
10     return ¬dsg.has_cycle(isolation_spec)
```

and *snapshot isolation*. It is easy to modify our checker to support additional isolation levels, as long as they can be expressed using the Adya model.

Algorithm 1 gives a high-level overview of the checking process, which involves two steps: (1) computing dependencies and (2) checking the resulting DSG. The process of computing dependencies is separated into computing item dependencies which is handled by `get_item_deps` (see Section 4.1) and predicate dependencies which is handled by `get_pred_deps` (see Section 4.2). These functions also detect all non-cyclic anomalies introduced by the Adya model [3], such as intermediate and aborted reads. In practice, database systems can exhibit anomalies that violate the assumptions of the Adya model, so we also check for the non-cyclic anomalies introduced by Elle [4] and for the result set mismatch anomaly that we introduced in Section 3.

Once Emme has computed all dependencies, it builds a DSG and checks it for cycles. Emme's cycle-detection algorithm takes the isolation level specification as input, since isolation levels differ in the types of cycles they allow. Additional dependencies exist that need to be computed for some isolation levels, for example, start-dependencies for *snapshot isolation*. Emme does support *snapshot isolation*, however, we omit these details from our general checking algorithm for simplicity.

4.1 Item Dependencies

The algorithm for computing the item dependencies of an operation is shown in Algorithm 2. In addition to computing the item dependencies, the algorithm must also detect all non-cyclic anomalies, such as aborted reads, that can occur from read and write operations. Our algorithm handles reads and writes separately.

Read operations are handled by `get_read_deps`. The `is_anomalous_read` function tries to detect four non-cyclic anomalies: (1) aborted reads and (2) intermediate reads which are defined in the Adya model, and (3) garbage reads and (4) internally inconsistent reads which are defined by Elle [4]. If there are no non-cyclic anomalies, then read dependencies and anti-dependencies are computed. A read dependency is created with the `add_read_dep` function, which creates a dependency from the transaction that wrote the version to the transaction that read it. The `add_anti_dependency` function creates an anti-dependency from the transaction that issued the read to the transaction that writes the next version in the version order after the version read.

Write operations are handled by `get_write_deps`. There is only one non-cyclic anomaly that can occur due to a write operation, which is a duplicate write. A duplicate write occurs when two separate write operations each create a new version of an object and both versions have the same value. Since we restrict versions to be uniquely identifiable through a combination of their object identifier and their value, a duplicate indicates something has gone wrong internally. Finally, a write dependency is created between the transaction that wrote the previous version in the version order and the transaction that issued the write operation with the current version.

Computing all item dependencies has time complexity proportional to the number of read and write operations in the history since it is necessary to iterate over all read and write operations.

4.2 Predicate Dependencies

Algorithm 3 outlines how predicate dependencies are computed. It starts by checking for a result set mismatch anomaly. As defined in Section 3, a result set mismatch anomaly occurs when the actual result set of an operation does not equal the result set returned when evaluating the predicate on the version set. Therefore, computing the expected results requires a predicate evaluation oracle, which we call the *matches* oracle. Given a test version and a predicate, the matches oracle returns true if the test version matches the predicate. We have designed two matches oracles with different tradeoffs.

The *database matches oracle* is the most basic oracle, as it uses the database system itself to evaluate the predicate. First, the test version replaces the version of the same object that was in the version set. Then, this modified version set is loaded into the database. Finally, the predicate is executed by the database and the oracle returns true if the test version is in the result set. The advantage of this approach is its simplicity and ease of implementation. However, it does require inserting a potentially large version set into the database for each call to the oracle, which can be expensive. The database matches oracle also assumes that the non-transactional

Algorithm 2: Compute the item dependencies from an operation.

```
1  Def get_item_deps(op, vo):
2      if op.is_read then
3          return get_read_deps(op, vo)
4      else
5          return get_write_deps(op, vo)
6
7  Def get_read_deps(op, vo):
8      deps = set()
9      if is_anomalous_read(result) then
10         raise read_anomaly()
11     add_read_dep(deps, op.result.tid, op.tid)
12     next_write = vo.get_subsequent_write(result)
13     if next_write ≠ null then
14         add_anti_dep(deps, op.tid, next_write.tid)
15     return deps
16
17 Def get_write_deps(op, vo):
18     deps = set()
19     if is_duplicate_write(op.result) then
20         raise duplicate_write_anomaly()
21     prev_write = vo.get_previous_write(op.result)
22     add_write_dep(deps, prev_write.tid, op.tid)
23     return deps
```

Algorithm 3: Compute the predicate dependencies from an operation.

```
1  Def get_pred_deps(op, vo):
2      deps = set()
3      expected_results = compute_results(op.query, op.version_set)
4      if expected_results ≠ op.results then
5          raise result_set_mismatch_anomaly()
6      objects = vo.get_all_objects()
7      for object ∈ objects do
8          vset_version = op.version_set.get(object)
9          for version ∈ object.versions do
10             prev = vo.previous_version(version)
11             if ¬changes_matches(op.query, version, prev) then
12                 continue
13             if vo.succeeds(version, vset_version) then
14                 add_pred_anti_dep(deps, op.tid, version.tid)
15             else
16                 add_pred_read_dep(deps, version.tid, op.tid)
17     return deps
18
19 Def compute_results(query, version_set):
20     results = set()
21     for version ∈ version_set do
22         if matches(query, version) then
23             results.add(version)
24     return results
25
26 Def changes_matches(query, version, prev_version):
27     prev_matches = matches(query, prev_version)
28     curr_matches = matches(query, version)
29     return prev_matches ≠ curr_matches
```

query evaluation part of the database is correct, but it does not assume that the concurrency control protocol implementation is correct. In practice, these parts of the database system implementation have little overlap. We believe this is reasonable as there are existing techniques [1, 6, 39–43] to validate the correctness of the query evaluator/optimizer and the focus of this work is on finding bugs in the implementation of concurrency control protocols.

The second matches oracle, which we call the *interpreter oracle*, uses a SQL interpreter to evaluate the predicate. Using a SQL interpreter instead of the database matches oracle makes the evaluation of each predicate significantly more efficient because the interpreter can evaluate the predicate without communicating with the database system. A major downside of this approach is the cost to implement the interpreter, which scales with the number of database features it needs to support, and also the ongoing maintenance required to keep the implementation in sync with any changes to the specification of the database system. This approach is inspired by pivoted query synthesis [41], which uses a database system specific SQL interpreter to execute a predicate condition to determine if a given row would match the predicate. This has been successfully applied to find hundreds of query evaluation bugs and implementations exist for many systems. We believe the use of a SQL interpreter for other database testing approaches demonstrates that the cost of implementing the SQL interpreter is worth it and can benefit various different testing approaches. We implemented a basic query evaluator that consists of roughly 100 lines of Python code, which we reused across each database system.

Once the matches oracle has been used to confirm that the result set matches the expected result set, it is necessary to iterate over all versions ever written in order to determine whether that version could change the matches of the predicate operation. If a version does not, then no dependencies exist for that version. If a version does change the matches, then the type of dependency created depends on where that version lies in the version order compared to the version from the same object in the version set. If the version comes after the version in the version set, then a predicate anti-dependency is added and if it is equal to or comes before the version set version in the version order, then a predicate read dependency is created.

Algorithm 3 computes the predicate dependencies for a single predicate operation. To compute all predicate dependencies, the algorithm is repeated for every predicate operation. This makes the predicate dependency computation expensive compared to item dependency computation. The cost is intrinsic to the Adya model's [3] data-driven definitions. The item dependency computation runs in time

$O(W + R)$ where W and R are the number of read and write operations in the history. The predicate computation runs in $O(P \cdot W)$ where P is the number of predicate operations in the history. This is exacerbated by predicate update operations causing additional individual write operations.

4.3 Black-box Checking

The Adya model assumes the existence of a version order and the required version sets. Furthermore, both are defined abstractly in terms of objects and versions. Therefore, once the version order and version sets have been recovered from the database, they can be used without any knowledge of how they were produced or of the underlying database system. This makes it possible to abstract away the version order and version set derivation and recovery process behind an API and work with them in a purely black-box fashion.

Working with the version order and version sets in a black-box fashion has two key advantages. Firstly, testers can be oblivious to the internals of the systems that they are writing tests for. This is particularly useful when testers are separated from the team that implemented the concurrency control protocol. Furthermore, regardless of who writes the tests, the test code itself need not be tied to the implementation details of either the version certificate recovery process or the concurrency control protocol. Secondly, this enables users of the database to gain assurance about the correctness of the system without needing access to its source code or knowledge of the concurrency control protocol used. This is particularly important when interacting with proprietary database systems and is a key motivation for the Cobra checker [45]. It is sufficient for the database system, perhaps through a verification interface, to output the version certificate, which the client can then input into our checker to validate that the database is upholding its contract. For isolation levels where checking is NP-complete, clients also obtain the guarantee that faking a version certificate, that is, outputting a version certificate that passes checking but in reality using one that does not, would require solving an NP-complete problem efficiently. We view this as a certificate of correctness from the database system.

5 Version Certificate Recovery

In order to check that an execution history conforms to some isolation level specification, it is necessary to first define the version certificate, which consists of both the expected version order and expected version sets, and then to recover it from the database system under test. To demonstrate that version certificate recovery is feasible in practice, we have implemented version certificate recovery for three real-world database systems: CockroachDB [44], TiDB [20], and PostgreSQL [35]. We chose these three systems because they are a mix of distributed and single-node systems and they each use a different concurrency control protocol. We did not modify any of the systems to enable our approach.

5.1 CockroachDB

CockroachDB is a distributed database system offering the *serializable* isolation level. CockroachDB assigns each transaction a unique hybrid logical clock timestamp [15] and guarantees that arranging transactions and their operations in ascending timestamp order will provide a valid serialization order. This is identical to the guarantees of the timestamp ordering protocol discussed in Section 2, so the expected version order can be defined as ascending timestamp order. The expected version set of an operation consists of the version of each object with the greatest timestamp less than or equal to the timestamp assigned to the reading transaction, or if the operation's transaction has modified an object, the latest version of the object modified by the transaction.

With the version certificate defined, it is necessary to recover it from the database. We leverage CockroachDB's `CHANGEFEED` mechanism to recover the versions written to the database along with their timestamps. The `CHANGEFEED` mechanism is implemented by aggregating information from each node's write-ahead log and providing it in any easy-to-consume format. Recovering information from a database system's write-ahead log is a common way of implementing some, if not all of version certificate recovery. Additionally, with the increasing popularity of change data capture as a general technique for recovering information from database systems, more and more systems are implementing this functionality, which makes implementing version certificate recovery significantly easier.

CockroachDB's `CHANGEFEED` mechanism provides only the final version of each object that is written by a transaction. If an object is updated twice within the same transaction, we will not recover the version resulting from the first update. This has no impact on checking item-only histories, as every item-only write operation can record which version it is writing, so it is possible to associate a timestamp with these writes regardless of whether or not we can recover them. However, for predicate updates, there is no way of knowing which versions were created due to the update as it depends on the versions that match the predicate condition.

Missing versions due to predicate updates can cause false positives in the general case due to the way the version set of an operation is computed. Therefore, to ensure that we can always recover all versions and their timestamps, we restrict CockroachDB transactions to only contain a predicate update if it contains no other write operations. This ensures that every version written by the predicate update must be the final version of an object written within the transaction and therefore will be reported by CockroachDB's `CHANGEFEED` mechanism. There are alternative strategies for dealing with this, such as scanning the entire contents of the database after each predicate update. Of course, it may still be possible to

modify CockroachDB to report intermediate writes, however, we wanted to demonstrate that it is possible to get a *useful* test setup with minimal effort.

The version certificate recovery implementation consists of roughly 200 lines of Python code, demonstrating the simplicity of the implementation.

5.2 TiDB

TiDB is a distributed hybrid transactional/analytical processing database system that offers *snapshot isolation* as its primary isolation level. For systems supporting *snapshot isolation*, such as TiDB, the version order is always chosen as the commit order of transactions [18]. The intuition for this is that updates in any *snapshot isolation* scheme are handled in one of two ways: (1) the first committer wins or (2) the first updater wins. Either scheme ensures a total order on versions that matches the commit order. This means that we can define the expected version order to be equal to the commit order of transactions.

To define the expected version sets, it is important to understand how *snapshot isolation* performs reads. In a system supporting *snapshot isolation*, all reads are performed at a start time $start(T_i)$. We can use $start(T_i)$ to define the expected version set of every operation in T_i. The expected version set of an operation performed at $start(T_i)$ is the set containing the version of each object whose timestamp is greatest and also less than or equal to $start(T_i)$, or the latest write by an operation in T_i if such an operation exists. Care has to be taken to use the correct timestamp for $start(T_i)$ as TiDB supports two transaction models that use different timestamps to perform reads: (1) optimistic, where transactions are rolled back only when there is a conflict, which defines a timestamp `start_ts` to act as $start(T_i)$ for reads, and (2) pessimistic, where transactions take locks during execution and start committing only after ensuring a transaction can be successfully executed, which uses the `for_update_ts` timestamp for reads. We set $start(T_i)$ to be either `start_ts` or `for_update_ts` depending on which model is used.

With both the expected version order and expected version sets defined, it is necessary to recover all versions written to the system, along with the `start_ts` for optimistic transactions and `for_update_ts` for pessimistic transactions. TiDB makes it easy to recover this information as it is exposed by an HTTP debugging API that will list each version and its timestamp. It does this by scanning the underlying multi-version concurrency control (MVCC) data store, a technique that we call heap-scanning. Similar to CockroachDB, TiDB's HTTP API reports only the final version of each object that is modified within a transaction, therefore, we also restrict a transaction to contain a predicate update only if there are no other writes within it. Alternatively, it is possible to recover version information using the TiDB change data capture tool, which operates on the write-ahead log (WAL) of each node in TiDB, similar to CockroachDB's `CHANGEFEED` mechanism. Our TiDB heap-scanning implementation of version certificate recovery consists of roughly 150 lines of Python, which demonstrates again the simplicity of the technique.

5.3 PostgreSQL

PostgreSQL is an MVCC RDBMS that supports multiple isolation levels. We focus on its *serializable* isolation level, which it provides using serializable snapshot isolation (SSI) [11, 33]. SSI is based on *snapshot isolation*, and uses the same underlying mechanisms as *snapshot isolation*, however, it adds an additional level of checks to prevent a transaction from committing if certain dangerous dependency structures [11] are present between transactions. These dependency structures are known to lead to *serializability* violations, so by preventing these, in addition to the properties provided by *snapshot isolation*, all histories produced are *serializable*.

Like *snapshot isolation*, picking the commit order of versions as the version order guarantees a *serializable* DSG in a correct execution [17]. This is because the checks introduced by SSI may prevent certain transactions from committing, but they do not alter the ordering of transactions once they have committed. Therefore, it is possible to define the expected version order as the commit order of transactions. To recover the version order, we leverage PostgreSQL's logical streaming replication and the Debezium change data capture tool. The primary benefit of using Debezium's CDC tool is that it abstracts the low-level details of PostgreSQL's WAL format and integrates with its logical replication protocol. This significantly reduces the effort required to implement version certificate recovery, with the implementation only just exceeding 300 lines of Python code.

In addition to recovering the version order, our approach also requires recovering the version set of each predicate operation. PostgreSQL uses an MVCC scheme along with a snapshot mechanism to determine the set of versions visible to an operation. At the *serializable* isolation level, each transaction uses a single snapshot to determine the set of visible versions for its operations. PostgreSQL defines a snapshot in three parts:

1. The smallest transaction ID, T_{min}, that is still active. The versions written by transactions with a smaller ID than T_{min} are visible (modulo issues with wraparound, which we do not discuss here, but can be handled).
2. The largest transaction ID, T_{max}, that is still active. The versions written by transactions with an ID greater than or equal to T_{max} are therefore not visible.
3. A list of active transaction IDs, `active_txs`, between T_{min} and T_{max}, whose versions are not visible.

PostgreSQL represents these snapshots in a condensed form of T_{min}: T_{max}: `active_txs`. The snapshot *100* : *104* : *100*, *102* means that 100 is the smallest active transaction ID, 104 is the largest active transaction ID and finally,

that transactions with ID 100 and 102 are active, so their versions are not visible.

In general, the visibility rules of PostgreSQL are complex. It is well-known that PostgreSQL does not support arbitrary logical time-travel queries, that is, the ability to ask for a consistent view of the database from the point of view of a historical transaction ID. However, we can simulate this for our specific use case of recovering an expected version set by using PostgreSQL's `pg_current_snapshot()` function [36].

For each predicate operation we record the snapshot used by calling the `pg_current_snapshot()` function. Then, a new transaction, which we call the *shadow transaction*, is started that shares the same snapshot using PostgreSQL's `SET TRANSACTION SNAPSHOT` command. To recover the version set, we then query all rows to see the latest visible version. While this is simple to implement, it requires running an additional transaction for every predicate operation in the history.

5.4 Generality

With some exceptions, concurrency control protocols can be grouped into categories of similar approaches [9, 49, 50]. There are arguably four main categories: (1) locking, (2) timestamp ordering, (3) optimistic concurrency control, and (4) certifier-based approaches. We have tried to cover as many of these as possible in our three implementations. TiDB uses locking in its pessimistic mode and optimistic concurrency control in its optimistic mode; PostgreSQL uses SSI which can be considered a certifier based approach; and finally, CockroachDB's core invariant is equivalent to that of a timestamp ordering protocol. We believe this shows that our approach is general. There will of course be differences between concurrency control protocols even within the same family, however, we expect that the above approaches can be adapted to cover most variations.

5.5 Limitations

Primarily, the goal of using version certificate recovery to test a system is to increase confidence in its correctness. Version certificate recovery does not aim to provide a guarantee that a system is free from bugs. As well as recognizing the benefits of version certificate recovery it is important to understand its limitations.

There were some practical limitations that we found when applying version certificate recovery to real systems. The first limitation that we encountered was that both CockroachDB and TiDB only report the last written version of each object within a transaction. This meant that we had to disallow any other write operations in transactions that contained a predicate update operation. The second limitation came from the decision to leverage existing functionality to recover some aspects of the version certificate. As a result of this, we rely on this functionality to be correct in order for our results to be valid. We believe this is a sensible trade-off as using this functionality significantly reduced the amount of effort necessary to implement version certificate recovery and also helps to decouple the version certificate recovery implementation from low-level details such as the WAL format.

In addition to the practical limitations, both Emme's soundness and completeness rely on a valid version certificate being presented. If the version certificate is created incorrectly then both false positives and false negatives can occur. This can happen either because of bugs in the mechanisms used to recover the version certificate e.g. a bug in CockroachDB's CDC functionality, or because the version certificate was specified incorrectly e.g. creating the version order in timestamp order for a serializable snapshot isolation system.

Algorithm 4: Check the expected serialization order of the recorded transactions.

```
1  Def check_expected_order(txns):
2      txns = sort_in_expected_order(txns)
3      parent_state = {}
4      for txn ∈ txns do
5          for op ∈ txn.ops do
6              if op.is_read then
7                  if ¬expected_results_match(parent_state, op) then
8                      return False
9              else
10                 new_writes = evaluate(parent_state, op)
11                 for write ∈ new_writes do
12                     parent_state[write.key] = write.value
13     return True
14
15 Def expected_results_match(parent_state, op):
16     expected_results = compute_results(op.query, parent_state)
17     return op.results == expected_results
```

6 Expected Serialization Order

As discussed in Section 4, a fundamental issue with using Adya's model as the basis for a checker is the $O(P \cdot W)$ cost of computing predicate dependencies. Furthermore, any checker using the Adya model needs to know both the version order and version sets associated with a history. This is not exposed by database systems, so the version certificate recovery approach presented in Section 5 is required to recover this information. While we argue the effort to achieve this is modest, for some *serializable* concurrency control protocols we can do better.

For many *serializable* protocols, it is possible to define an expected total order on transactions such that for any execution of the protocol, arranging transactions in that order ensures that they are *serializable*. We call this an *expected serialization order*. For example, Section 2 shows a timestamp ordering protocol that guarantees transactions will always be *serializable* in ascending timestamp order. Commitment

ordering protocols [37], such as strong strict two-phase locking, have an expected serialization order equal to the commit ordering. For optimistic protocols, it is possible to define an expected serialization order by arranging transactions in the order of their validation timestamps. However, there are some *serializable* protocols, such as serializable snapshot isolation (SSI) where it is not possible, at least by default, to define an expected serialization order. Nevertheless, it is possible to modify many variants of SSI to record a *serializable* ordering if required [30].

We implement the expected serialization order approach for CockroachDB. CockroachDB guarantees that arranging transactions in ascending timestamp order will guarantee *serializability*, therefore we can define the expected serialization order this way. Notice that this is much simpler than defining an expected version order and expected version sets. All that is needed to recover the expected serialization order is to recover each transaction's timestamp. For CockroachDB, we modified the test client to have each transaction record its own timestamp. Finally, we can sort transactions by their timestamp and pass them to Emme for verification.

Checking an expected serialization order. Intuitively, to check that the history is *serializable* when arranged in the expected serialization order, we should be able to replay each transaction and check that the results of any read operations match those that were observed in the history. Crooks et al. [13] formalize this idea and define *serializability* in terms of first-order logic predicates over a total order of transactions. Effectively, to check that a total order of transactions is *serializable*, a "current state" of the database is maintained and each transaction is replayed, with write operations updating the "current state". Each read operation is checked to ensure that it is valid at the "current state". If not, then that particular transaction ordering is rejected. Their formalization does not contain predicate operations, however, it can naturally be extended for *serializability* by handling predicate updates and reads in the same way as normal reads and writes, and their proof sketch can be modified to include predicate dependencies without changing its structure.

We extended Emme to enable checking an expected serialization order based on Algorithm 4. As with Emme's Adya-based checker, we require a matches oracle to evaluate predicates. We use our interpreter described in Section 4. The time complexity of checking is reduced as it is only required to evaluate each predicate on the writes in the "current state" rather than on every write. As Section 7 shows, this significantly improves both the performance and scalability of checking histories with predicate operations, and is a major advantage of the expected serialization order approach.

Whilst we have focused on *serializable* protocols in this section, Crooks et al. [13] define weaker isolation levels in terms of first-order logic predicates that must hold over some total order of transactions, so it may also be possible to define an expected total order for some weaker protocols too.

7 Evaluation

We evaluate (1) the effectiveness and performance of three implementations of version certificate recovery for PostgreSQL, TiDB, and CockroachDB; (2) the performance of our checker Emme on histories produced from PostgreSQL; and (3) the performance of the expected serialization technique on histories produced from CockroachDB. All experiments are carried out on a machine with a hexa-core Ryzen 1600 processor, 32 GB RAM, a WD Blue SN570 2 TB SSD, and an Ubuntu 20.04 LTS operating system. We use PostgreSQL 13.3 and run it on a single node. We use TiDB 5.3.0 and use the recommended cluster topology (three PD nodes, three TiKV nodes, and two TiDB nodes). We use CockroachDB v21.2.17 and run three nodes.

7.1 Version Certificate Recovery

In this subsection, we evaluate the effectiveness and performance of the version certificate recovery implementations described in Section 5. We considered all three version certificate recovery implementations: (1) log-based change data capture (CDC) for CockroachDB using their `CHANGEFEED` mechanism, (2) log-based CDC for PostgreSQL using the Debezium CDC tool [14], and (3) heap-scanning for TiDB.

Effectiveness. We demonstrate that version certificate recovery can find known bugs in existing systems. Firstly, we were able to demonstrate that version certificate recovery could find a known error in PostgreSQL 12.3's *serializable* isolation level [34]. The error is a well-known isolation anomaly that can occur in serializable snapshot isolation implementations [33]. Secondly, we asked a CockroachDB engineer to create three versions of CockroachDB [44], each with a bug that would violate its *serializability* guarantee. To avoid biases, we avoided inspecting the changes to CockroachDB before attempting to find each bug. Version certificate recovery was able to detect all three bugs. This shows that version certificate recovery is effective at detecting isolation level anomalies in real-world database systems. Finally, we demonstrate that our approach can find predicate-only anomalies that Elle—a state-of-the-art checker—cannot. To do this, we executed patterns of transactions that are highly likely to produce predicate-only anomalies when run at the *read committed* isolation level. We executed these using PostgreSQL and tried to validate them at the *serializable* isolation level. Emme was able to detect these predicate-only anomalies and rejected them as invalid, however, Elle could not detect these and accepted them as *serializable* histories. This clearly shows the importance of being able to check histories for predicate anomalies.

Performance. For each version certificate recovery implementation, we measured the execution time of both the test

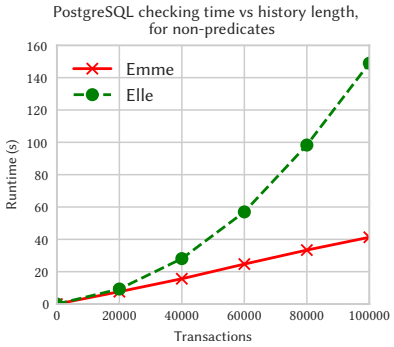

Figure 8. Comparison of history size and the execution time of item dependency verification in the Emme and Elle verifiers. Each transaction executed five non-predicate operations.

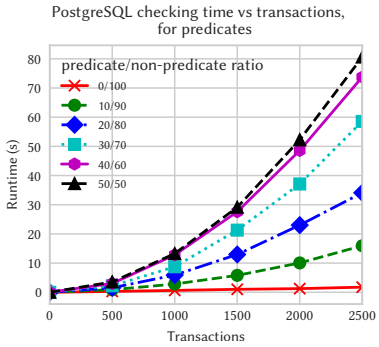

Figure 9. Comparison of history size and the execution time of mixed item and predicate dependency verification in the Emme verifier. Each transaction executed a mix of five predicate and non-predicate operations. Different ratios of predicate to non-predicate operations were chosen.

client and the version certificate recovery process to confirm that the time spent recovering the version certificate was less than the history generation time. This demonstrates that it is possible to hide the cost of version certificate recovery behind that of the test client. However, for ease of implementation, all version certificate recovery implementations recover the version order and version sets after the test clients finish executing. Nevertheless, it would be possible to have an implementation of version certificate recovery that runs alongside the test client execution.

7.2 Performance Characteristics of Emme

To examine the performance characteristics of Emme, we carried out two experiments. The first compares the performance of Emme and Elle on histories containing only non-predicate operations and the second demonstrates the performance of Emme on histories containing predicate operations. All experiments use a single table with three columns. Insert operations use an `ON CONFLICT ... DO UPDATE` clause, which will update a key if it already exists in the table. Increment operations are implemented as a read operation followed by an update operation, which captures a read-modify-write pattern that is common in real transactions. Predicate histories contain basic range queries such as `SELECT c0, c1 FROM table WHERE c1 >= 0 AND c1 <= 10`, as well as aggregate operations min and max.

Fig. 8 compares how both Emme and Elle scale with the history size when verifying histories without predicate operations. The execution time is solely comprised of the verification time. The experiment used a mix of 30% updates, 40% reads, 20% increments, and 10% inserts, which gives a 50/50 read/write ratio. We limit the number of keys inserted to 1000. Emme performs similarly to Elle for smaller history sizes, but then starts to outperform Elle as the history size increases. We believe this is due to Elle's requirement to use list-append operations, which causes all reads to contain their full version order history as a list. As the history increases in size, each key accumulates increasingly many versions, which makes processing each read progressively more expensive.

Fig. 9 shows how the ratio of predicate and non-predicate operations in a history affects Emme's checking performance. The experiment used an operations mix of 10% insert operations and a 50/50 ratio of reads and updates for both key-value and predicate operations. The number of keys was set to a maximum of 100. Predicate checking has $O(P * V)$ complexity, where P is the number of predicates in the history and V is the total number of versions. The graph shows this empirically, with both the number of transactions (and therefore the number of versions) and the number of predicate operations causing an increase in execution time as they themselves increase. This highlights the performance limitations of predicate checking due to the Adya model's data-driven definitions of predicate anomalies. Nevertheless, Emme is still able to verify moderately large histories in a time frame that is acceptable for testing.

7.3 Expected Serialization Order

We extended Emme to support checking using the expected serialization order technique and refer to this mode as the *Expected SER checker*. To demonstrate that the Expected SER checker is as effective as Emme, we ensured that it could detect all three errors in the modified versions of CockroachDB.

Performance. A key benefit of using Expected SER checking is its superior performance. Fig. 10 compares the performance of the Expected SER checker to that of Elle and Emme using item-only histories generated from CockroachDB. Although the Expected SER checker still scales linearly with the history size, its execution time grows significantly slower than that of both Elle and Emme. The Expected SER checker

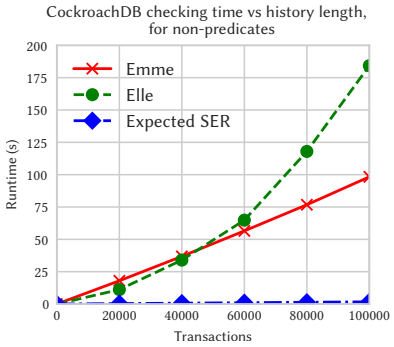

Figure 10. Comparison of history size and checking time for the Elle, Emme, and the Expected SER checkers using item-only histories. The same mix of operations as Fig. 8 was used.

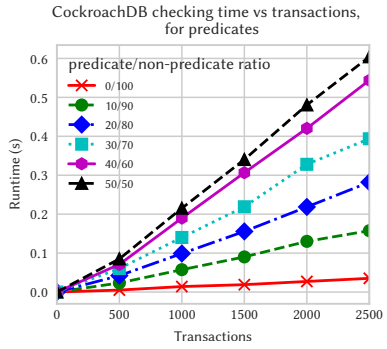

Figure 11. Comparison of the effect of both increasing history size and increasing the mix of predicate operations on the checking time of the Expected SER checker for histories produced from CockroachDB.

verifies a 100,000 transactions history in only 1.7 seconds compared to 98.3 seconds it takes Emme, and 184.2 seconds it takes Elle.

The Expected SER checker has the most pronounced speedup for histories containing predicate operations. It checks a history containing 2500 transactions in only 0.6 seconds, compared to 76.2 seconds taken by Emme. Fig. 11 shows how the execution time of the Expected SER checker changes as both the history size and proportion of predicate operations changes. Unlike Emme's predicate checking performance (Fig. 9), the Expected SER checker's performance scales linearly with the history size when holding the proportion of predicate operations constant. This makes it suitable for checking large histories containing predicate operations.

8 Related Work

Formal models of isolation levels. ANSI SQL-92 [5] formally defines four transaction isolation levels that compliant systems can offer: *read uncommitted*, *read committed*, *repeatable read*, and *serializable*. These levels are defined in terms of the presence of three phenomena: dirty reads, non-repeatable reads, and phantom reads. Building on previous work [19] Berenson et al. [7] show that the absence of the three phenomena defined in ANSI SQL does not guarantee *serializable* execution. They define stricter versions of the ANSI SQL phenomena and formalize two additional isolation levels called *cursor stability* and *snapshot isolation*. Bernstein [8, 9] defines *serializability* in terms of dependency graphs and a version order. Adya et al. [2, 3] extend this model to support a wider range of isolation levels and systems. Departing from dependency graphs, recent work has moved away from defining isolation levels in terms of ordering low-level operations and instead focuses on more declarative definitions [12, 13, 47].

Testing and Verification of Isolation Levels. Hermitage [23] provides a set of fixed test cases that demonstrate the behavior of various database systems at different isolation levels. PostgreSQL [35] uses a tool called Isolationtester to run a select set of interleavings for manually-written tests to find bugs in its implementation of various isolation levels.

In general, *serializability* checking is NP-Complete [31]. Biswas and Enea [10] provide exponential-time checkers for *prefix consistency*, *snapshot isolation*, and *serializability*, whilst providing polynomial-time checkers for *read committed* and *casual consistency*. Cobra [45] is an SMT solver based approach for verifying the *serializability* of key-value histories. It uses various heuristics to optimize checking speed on certain workloads, however, in the worst case still has exponential running time. Elle [4] is a checker based on the Adya model of isolation levels. It supports a variety of isolation levels and has successfully found bugs in real-world systems. To work efficiently, Elle requires the database system to support atomic list-append operations. Histex [26] is a gray-box approach to testing isolation level implementations. To the best of our knowledge, Histex is the only system—other than ours—that can check histories that include predicate operations. However, these histories must have been produced by a single-version system running a locking protocol, so Histex only works for a very narrow set of systems, and therefore, we do not compare our checker against it.

9 Conclusion

We have shown that it is possible to define and recover a version certificate consisting of an expected version order and set of expected version sets for three widely used database systems—TiDB, PostgreSQL, and CockroachDB. Our checker Emme, supports checking both the *serializability* and *snapshot isolation* of execution histories using the recovered version certificate, which makes Emme the first general-purpose checker that can check histories containing predicate operations. We have shown that version certificate recovery is an effective validation method by demonstrating that it can identify invalid histories caused by a known bug

in an older version of PostgreSQL's *serializability* implementation and caused by three bugs in a fork of CockroachDB's *serializability* implementation that were introduced purposefully by a CockroachDB engineer. Finally, we introduced the notion of an expected serialization order and described how it can be applied to a range of *serializable* concurrency control protocols without needing to define and recover a version certificate. Furthermore, using the expected serialization order technique leads to faster checking performance and better scalability for checking histories with predicate operations. We demonstrate this by implementing the technique for CockroachDB and finding that it can check predicate histories 53×–120× faster than Emme.

Acknowledgments

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