Fast Failure Recovery for Main-Memory DBMSs on Multicores

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ABSTRACT

Main-memory database management systems (DBMS) can achieve excellent performance when processing massive volume of on-line transactions on modern multi-core machines. But existing durability schemes, namely, tuple-level and transaction-level logging-and-recovery mechanisms, either degrade the performance of transaction processing or slow down the process of failure recovery. In this paper, we show that, by exploiting application semantics, it is possible to achieve speedy failure recovery without introducing any costly logging overhead to the execution of concurrent transactions. We propose PACMAN, a parallel database recovery mechanism that is specifically designed for lightweight, coarse-grained transaction-level logging. PACMAN leverages a combination of static and dynamic analyses to parallelize the log recovery: at compile time, PACMAN decomposes stored procedures by carefully analyzing dependencies within and across programs; at recovery time, PACMAN exploits the availability of the runtime parameter values to attain an execution schedule with a high degree of parallelism. As such, recovery performance is remarkably increased. We evaluated PACMAN in a fully-fledged main-memory DBMS running on a 40-core machine. Compared to several state-of-the-art database recovery mechanisms, PACMAN can significantly reduce recovery time without compromising the efficiency of transaction processing.

1. INTRODUCTION

The on-going evolution of modern computer architectures has led to the rapid development of main-memory DBMSs. By resolving potential performance bottlenecks such as disk accesses and centralized contention points, modern main-memory DBMSs can power OLTP applications at very high throughput of millions of transactions per second on a multi-core machine [15, 17, 18, 40].

However, system robustness can be the Achilles' heel of such DBMSs. To preserve durability, a DBMS continuously persists transaction logs during execution to ensure that the database can be restored to a consistent state after a failure, with all the committed transactions reflected correctly.

Existing approaches for DBMS logging can be broadly classified into two categories, each characterized by different granularities and performance emphasis. Originally designed for disk-based DBMSs, *tuple-level logging* schemes, which include *physical logging* (a.k.a. data logging) and *logical logging* (a.k.a. operation logging)[1], propagate every tuple-level modification issued from a transaction to the secondary storage prior to the transaction's final commitment [25]. Such a heavyweight, fine-grained approach can generate tens-of-gigabyte of logging data per minute, causing over 40% performance degradation for transaction execution in a fast main-memory DBMSs [24, 48]. However, from the perspective of database recovery, tuple-level log recovery can be easily performed in parallel, and the recovery time can be further reduced by applying the last-writer-wins rule (a.k.a. Thomas write rule [48]). As an alternative to tuple-level logging, *transaction-level logging*, or *command logging* [24], is initially invented for main-memory DBMSs that leverage deterministic execution model for processing transactions [17, 38, 39]. In contrast to common practice, most transactions in this type of DBMSs are issued from predefined *stored procedures*. In this scenario, transaction-level logging can simply dump transaction logic, including a stored procedure identifier and the corresponding query parameters, into secondary storage. This coarse-grained strategy incurs very low overhead to in-memory transaction processing. However, it also significantly slows down the recovery process, as transaction-level log recovery is widely believed to be hard to parallelize [24, 48]. To achieve high performance in both transaction processing and failure recovery, recent efforts have largely focused on exploiting new hardware (e.g., non-volatile memory) to minimize the runtime overhead caused by tuple-level logging [16, 29, 41, 48].

In this paper, we present PACMAN, a parallel failure recovery mechanism that is specifically designed for lightweight, coarse-grained transaction-level logging in the context of main-memory multi-core DBMSs. The design of PACMAN is inspired by two observations. First, DBMSs utilizing transaction-level logging issue transactions from stored procedures. This allows PACMAN to analyze the stored procedures to understand the application semantics. Second, DBMSs recover lost database states by re-executing transactions in their original commitment order, and this order is determined before system crash. This allows PACMAN to parallelize transaction-level log recovery by carefully leveraging the dependencies within and across transactions.

PACMAN models the transaction-level log recovery as a *pipeline of data-flow processing*. This is accomplished by incorporating a combination of static and dynamic analyses. At compile time, PACMAN conservatively decomposes a collection of stored procedures into multiple conflict-free units, which are organized into a dependency graph that captures potential *happen-before* relations. This prior knowledge enables fast transaction-level log recovery with a

[1] In this paper, we follow the definitions presented in [13].

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high degree of parallelism, and this is achieved by generating an execution schedule through exploiting the availability of the runtime parameter values of the lost transactions.

Unlike many state-of-the-art database logging-and-recovery schemes [16, 29, 41, 48], PACMAN does not make any assumption on the performance of the underlying hardware. It is also orthogonal to data layouts (e.g., single-version or multi-version, row-based or column-based) and concurrency control schemes (e.g., two-phase locking or timestamp ordering), and can be applied to many main-memory DBMSs, such as Silo [40] and Hyper [18]. PACMAN's analysis approach also departs far from the existing, purely static, program partitioning and transformation techniques [7, 30, 32, 36], in that PACMAN yields a program decomposition that is especially tailored for the execution of pre-ordered transaction sequences, and a higher degree of parallelism is attained by incorporating runtime information during failure recovery.

In contrast to the existing transaction-level log recovery mechanism [24] that relies on partitioned data storage for parallelization (i.e., two transaction-level logs from different transactions accessing different data shards could be replayed in parallel), PACMAN is the first parallel recovery mechanism for transaction-level logging scheme that goes beyond partitioned-data parallelism. Specifically, PACMAN innovates with a combination of static and dynamic analyses that enable multiple recovery operations to be parallelized even when accessing the same data shard.

We implemented PACMAN as well as several state-of-the-art recovery schemes in Peloton [31], a fully fledged main-memory DBMS optimized for high-performance multi-core transaction processing. Through a comprehensive experimental study, we spotted several performance bottlenecks of existing logging-and-recovery schemes for main-memory DBMSs, and confirmed that PACMAN can significantly reduce recovery time without bringing any costly overhead to transaction processing.

We organize the paper as follows: Section 2 reviews durability techniques for main-memory DBMSs. Section 3 provides an overview of PACMAN. Section 4 demonstrates how PACMAN achieves fast failure recovery with a combination of static and dynamic analyses. Section 5 discusses the potential limitations of PACMAN. We report extensive experiment results in Section 6. Section 7 reviews related works and Section 8 concludes.

2. DBMS DURABILITY

A main-memory DBMS employs *logging* and *checkpointing* mechanisms during transaction execution to guarantee the durability property.

2.1 Logging

A main-memory DBMS continuously records transaction changes into secondary storage so that the effects of committed transactions can persist even in the midst of system crash. Based on the granularity, existing logging mechanisms for main-memory DBMSs can be broadly classified into two categories: *tuple-level logging* and *transaction-level logging*.

Initially designed for disk-based DBMSs, tuple-level logging keeps track of the images of modified tuples and persists them into secondary storage before the transaction results are returned to the clients. According to the types of log contents, tuple-level logging schemes can be further classified into two sub-categories: (1) *physical logging*, which records the physical addresses and the corresponding tuple values modified by a transaction; and (2) *logical logging*, which persists the write actions and the parameter values of each modification issued by a transaction. Although logical logging usually generates smaller log records compared to physical logging, its assumption of *action consistency* [13], which requires each logical operation to be either completely done or completely undone, renders it unrealistic for disk-based DBMSs. Hence, many conventional disk-based DBMSs including MySQL [1] and Oracle [3] adopt a combination of physical logging and logical logging, or called *physiological logging*, to minimize log size while addressing action inconsistency problem. While disk-based DBMS leverages *write-ahead logging* to persist logs before the modification is applied to the database state, main-memory DBMSs can delay the persistence of these log records until the commit phase of a transaction [10, 48]. This is because such kind of DBMSs maintain all the states in memory, and dirty data is never dumped into secondary storage. This observation makes it possible to record only after images of all the modified tuples for a main-memory DBMS, and logical logging can be achieved, as the action inconsistency problem in disk-based DBMSs never occurs in the main-memory counterparts.

Transaction-level logging, or *command logging*, is a new technique that is initially designed for deterministic main-memory DBMSs [24]. As this type of DBMSs require the applications to issue transactions as stored procedures, the logging component in such a DBMS therefore only needs to record coarse-grained transaction logic, including the stored procedure identifier and the corresponding parameter values, into secondary storage; updates of any aborted transactions are discarded without being persisted. A well-known limitation of transaction-level logging is that the recovery time can be much higher compared to traditional tuple-level logging schemes, and existing solutions resort to replication techniques to mask single-node failures. The effectiveness of this mechanism, however, is heavily dependent on the networking speed, which in many circumstances (e.g., geo-replicated) is unpredictable [8].

A major optimization for DBMS logging is called *group commit* [9, 12], which groups multiple log records into a single large I/O so as to minimize the logging overhead brought by frequent disk accesses. This optimization is widely adopted in both disk-based and main-memory DBMSs.

2.2 Checkpointing

A main-memory DBMS periodically persists its table space into secondary storage to bound the maximum recovery time. As logging schemes in main-memory DBMSs do not record before images of modified tuples, these DBMSs must perform transactionally-consistent checkpointing (rather than fuzzy checkpointing [21]) to guarantee the recovery correctness. Retrieving a consistent snapshot in a multi-version DBMS is straightforward, as the checkpointing threads in this kind of DBMSs can access an older version of a tuple in parallel with any active transaction, even if the transaction is modifying the same tuple. However, for a single-version DBMS, checkpointing must be explicitly made asynchronous without blocking on-going transaction execution [17, 18, 48].

The checkpointing scheme in a DBMS must be compatible with the adopted logging mechanism. While physical logging requires the checkpointing threads to persist both the content and the location of each tuple in the database, logical logging and command logging only require recording the tuple contents during checkpointing.

2.3 Failure Recovery

A main-memory DBMS masks outages using persistent checkpoints and recovery logs. Once a system failure occurs, the DBMS recovers the most recent transactionally-consistent checkpoint from the secondary storage. To recover the checkpoints persisted for physical logging, the DBMS only needs to restore the table space, and the database indexes can be reconstructed lazily at the end of the subsequent log recovery phase. However, recovering the checkpoints persisted for logical logging and command logging requires the DBMS to reconstruct the database indexes simultaneously with the table space restoration. After checkpoint recovery completes, the DBMS subsequently reloads and replays the durable log sequences according to the transaction commitment order, in which manner the DBMS can reinstall the lost updates of committed transactions correctly.

2.4 Performance Trade-Offs

Based on the existing logging-and-recovery mechanisms, it is difficult to achieve high performance in both transaction processing and failure recovery in a main-memory DBMS: fine-grained tuple-level logging lowers transaction rate since more data is recorded; coarse-grained transaction-level logging slows down failure-recovery phase as it incurs high computation overhead to replay the logs [24, 48]. As we shall see, our proposed PACMAN offers fast failure recovery without introducing additional runtime overhead.

3. PACMAN OVERVIEW

PACMAN aims at providing fast failure recovery for modern main-memory DBMSs that execute transactions as stored procedures [17, 38, 39]. A stored procedure is modeled as a *parameterized transaction template* identified by a unique name that consists of a structured flow of database operations. For simplicity, we respectively abstract the *read* and *write* operations in a stored procedure as `var←read(tbl, key)` and `write(tbl, key, val)`. Both operations search tuples in the table `tbl` using the candidate key called `key`. The read operation assigns the retrieved value to a local variable `var`, while the write operation updates the corresponding value to `val`. Insert and delete operations are treated as special write operations. A client issues a request containing a procedure name and a list of arguments to initiate the execution of a *procedure instance*, called a *transaction*. The DBMS dispatches a request to a single *worker* thread, which executes the initiated transaction to either commit or abort.

PACMAN is designed for transaction-level logging [24] that minimizes the runtime overhead for transaction processing. The DBMS spawns a collection of *logger* threads to continuously dump committed transactions to the secondary storage. To limit the log file size and facilitate parallel recovery, the DBMS stores log entries into a sequence of files referred to as *log batches*. Each log entry records the stored procedure being invoked together with its input parameter values. The entries in each log batch are strictly ordered according to the transaction commitment order. The sequence of log batches are reloaded and processed in order during recovery.

Both the logging and log reloading can be performed in parallel, and we refer to Appendix A for detailed discussions. In this paper, we focus on parallelizing the replay of the logs generated by transaction-level logging.

The workflow of PACMAN is summarized in Figure 1. At compile time, PACMAN performs a static analysis of the stored procedures to identify opportunities for parallel execution. This analysis is performed in two stages. In the first stage, each stored procedure is analyzed independently to identify the flow and data dependencies among its operations. A flow dependency between two operations constrains the execution ordering between these operations, while a data dependency between two operations indicates that these operations could potentially conflict (i.e., one is reading and the other is writing the same tuple). Based on the identified dependencies, the stored procedure is segmented into a maximal set of smaller pieces which are organized into a directed acyclic graph, referred to as a *local dependency graph*. This graph explicitly captures the possible parallelization opportunities as well as the execution ordering constraints among the pieces. In the second stage, the local dependency graphs derived from the stored procedures are integrated into a single dependency graph, referred to as a *global dependency graph*. This graph captures execution ordering among the different subsets of pieces from all the procedures.

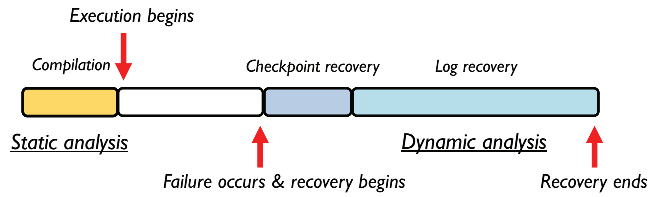


Figure 1: Workflow of PACMAN.

During recovery, PACMAN generates an execution schedule for each log batch using the global dependency graph. A straightforward approach to replay the log batches would be executing the schedules serially following the order of the log batches. For each schedule, instantiations of the stored procedure pieces could be executed in parallel following the execution ordering constraints derived from the global dependency graph.

To go beyond the execution parallelism obtained from static analysis, PACMAN further applies a dynamic analysis of the generated execution schedules to obtain a higher degree of parallelism in two ways. First, by exploiting the availability of the runtime procedure parameter values, PACMAN enables further intra-batch parallel executions. Second, by applying a pipelined execution optimization, PACMAN enables inter-batch parallel executions where different log batches are replayed in parallel.

In the following section, we discuss the design of PACMAN in detail.

4. PACMAN DESIGN

PACMAN achieves speedy failure recovery with a combination of static and dynamic analyses. In this section, we first show how PACMAN leverages static analysis to extract flow and data dependencies out of predefined stored procedures at compile time (Section 4.1). We then explain how the static analysis can enable coarse-grained parallel recovery (Section 4.2). After that, we discuss how dynamic analysis is used to achieve a high degree of parallelism during recovery time (Section 4.3 and Section 4.4). We further elaborate how PACMAN recovers ad-hoc transactions without degrading the performance (Section 4.5).

4.1 Static Analysis

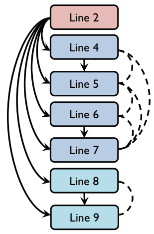
PACMAN performs static analysis at compile time to identify parallelization opportunities both within and across transactions. This is captured through detecting the flow and data dependencies within each stored procedure and among different stored procedures.

4.1.1 Intra-Procedure Analysis

PACMAN statically extracts operation dependencies from each stored procedure and constructs a *local dependency graph* to characterize the execution ordering constraints among the operations in the procedure. The corresponding algorithm is presented in Appendix B. Following classic program-analysis techniques [28, 43,

```
1. PROCEDURE Transfer(src, amount){
2.    dst<-read(Family, src, Spouse)
3.    if(dst!="NULL"){
4.       srcVal<-read(Current, src)
5.       write(Current, src, srcVal-amount)
6.       dstVal<-read(Current, dst)
7.       write(Current, dst, dstVal+amount)
8.       bonus<-read(Saving, src)
9.       write(Saving, src, bonus+1)
10.   }
11. }
```

(a) Stored procedure.



(b) Dependencies.

Figure 2: Bank-transfer example. (a) Stored procedure. (b) Flow (solid lines) and data (dashed lines) dependencies.

```
PROCEDURE Transfer(src, amount){
   // Slice T1
   dst<-read(Spouse, src)
   // Slice T2
   if(dst!="NULL"){
      srcVal<-read(Current, src)
      write(Current, src, srcVal-amount)
      dstVal<-read(Current, dst)
      write(Current, dst, dstVal+amount)
   }
   // Slice T3
   if(dst!="NULL"){
      bonus<-read(Saving, src)
      write(Saving, src, bonus+1)
   }
}
```

Figure 3: Procedure slices in bank-transfer example.

45], PACMAN identifies *flow dependencies* that capture two types of relations present in the structured flow of a program: (1) define-use relation between two operations where the value returned by the preceding operation is used as input by the following operation; (2) control relation between two operations where the output of the preceding operation determines whether the following operation should be executed. Flow dependencies are irrelevant to operation type (e.g., read, write, insert, or delete), and any operation can form flow dependencies with its preceding operations.

These two relations indicate the *happen-before* properties among operations, and *partially* restrict the execution ordering of the involved operations in a single stored procedure. To illustrate these dependencies, consider the pseudocode in Figure 2a resembling a bank-transfer example. This stored procedure transfers an amount of money from a user's current account to her spouse's account, and adds one dollar bonus to the user's saving account. We say that the operation in Line 5 is *flow-dependent* on that in Line 4, because the write operation uses the variable `srcVal` defined by the preceding read operation. Operations in Lines 4-9 are flow-dependent on the preceding read operation in Line 2 that generates the variable `dst`, which is placed on the decision-making statement in Line 3.

Classic program-analysis techniques, including points-to analysis [37] and control-dependency analysis [4], can efficiently extract flow dependencies from stored procedures, and two flow-independent operations can be potentially executed in parallel at runtime [5]. However, such analysis approaches ignore the data conflicts inherited in database accesses. To address this problem, PACMAN further identifies *data dependencies* among operations to capture their potential ordering constraints. Specifically, we say that two operations are *data-dependent* if both operations access the same table and at least one of them is a modification operation. Note that an insert or a delete operation can also form data-dependent relations with other operations if both operate on the same table. In the bank-transfer example, operations in Lines 4 and 5 are mutually data-dependent because they both access the `Current` table and one of them updates the table. All the dependencies in bank-transfer example are illustrated in Figure 2b.

The flow dependencies and data dependencies altogether can constrain the execution ordering of the database operations in a single stored procedure. However, they differ in detailed semantics. A flow dependency captures *must-happen-before* semantics, meaning that a certain operation can never be executed until its flow-dependent operations have finished execution. In contrast, a data dependency in fact only captures *may-happen-before* semantics, and runtime information can be incorporated to relax this constraint, as will be elaborated in Section 4.3.

Based on these dependencies, PACMAN decomposes each procedure into a maximal collection of parameterized units called *procedure slices* (or *slices* for short) that satisfy the following two properties: (1) each slice is a segment of a procedure program such that mutually data-dependent operations are contained in the same slice, and (2) whenever two operations x and y are in the same slice such that y is flow-dependent on x, then any operation that is between x and y must also be contained in that slice. Figure 3 shows the decomposition of the bank-transfer example into three slices (denoted by T_1, T_2, and T_3).

The set of slices decomposed from a stored procedure can be represented by a directed acyclic graph referred to as a *local dependency graph*. The nodes in the graph correspond to the slices; and there is a directed edge from one slice s_i to another slice s_j if there exists some operation o_j in s_j that is flow-dependent on some operation o_i in s_i. The local dependency graph captures the execution order among the slices in the procedure as follows: for any two distinct slices s_i and s_j in the graph, s_i must be executed before s_j if s_i is an ancestor of s_j in the graph; otherwise, both slices could be executed in parallel if s_i is neither an ancestor nor a descendant of s_j in the graph.

Figure 5a illustrates the local dependency graph for the Transfer procedure in the bank-transfer example. Observe that the operations in Lines 4-7 of Figure 2a are put into the same slice T_2 because these operations are mutually data-dependent. Slices T_2 and T_3 are both flow-dependent on T_1 because the operations in T_2 and T_3 cannot be executed until the variable `dst` has been assigned in the preceding read operation in Line 2.

4.1.2 Inter-Procedure Analysis

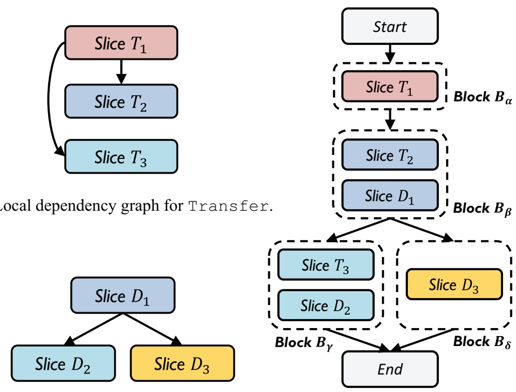
PACMAN further performs inter-procedure analysis to identify operation dependencies among the stored procedures. These dependencies are represented by a *global dependency graph* which is formed by integrating the local dependency graphs from all the stored procedures. The detailed algorithm is presented in Appendix B.

Before we formally define a global dependency graph, we first extend the definition of data-dependent operations to data-dependent slices. Given two procedure slices s_i and s_j, where s_i and s_j are slices from two distinct stored procedures, we say that these slices are *data-dependent* if s_i contains some operation o_i, s_j contains some operation o_j, and both operations are data-dependent.

The global dependency graph G for a set of stored procedures P is a directed acyclic graph where each node v_i in G represents a subset of procedure slices from the local dependency graphs associated with P. There is a directed edge from a node v_i to another node v_j in G if v_i contains some slice s_i, v_j contains some slice

```
PROCEDURE Deposit(name, amount, nation){
   // Slice D1
   tmp<-read(Current, name)
   write(Current, name, tmp+amount)
   // Slice D2
   if(tmp+amount>10000){
      bonus<-read(Saving, name)
      write(Saving, name, bonus+0.02*tmp)
   }
   // Slice D3
   if(tmp+amount>10000){
      count<-read(Stats, nation)
      write(Stats, nation, count+1)
   }
}
```

Figure 4: Procedure slices in bank-deposit example.



(a) Local dependency graph for `Transfer`.

(b) Local dependency graph for `Deposit`. (c) Global dependency graph.

Figure 5: (a) and (b): Local dependency graphs for `Transfer` and `Deposit` procedures. (c): Global dependency graph. Slices within the same dashed rectangle belong to the same block. Solid lines represent inter-block dependencies.

s_j, and both s_i and s_j are from the same stored procedure such that s_j is flow-dependent on s_i. The nodes in G satisfy the following four properties: (1) each slice in P must be contained in exactly one node in G; (2) two slices that are data-dependent must be contained in the same node; (3) if two nodes in G are reachable from each other, these two nodes are merged into a single node; and (4) if a node contains two slices from the same stored procedure, these two slices are merged into a single slice.

For convenience, we refer to the set of slices associated with each node in G as a *block*, and we say that a block B_j is *dependent* on another block B_i in G if there is a directed edge from B_i to B_j.

While a local dependency graph captures only the execution ordering constraints among slices from the same stored procedure, a global dependency graph further captures the execution ordering constraints among slices from different stored procedures. Specifically, for any two slices s_i and s_j in G, where s_i is contained in block B_i and s_j is contained in block B_j, s_i must be executed before s_j if B_i is an ancestor of B_j in G; otherwise, both slices could be executed in parallel if B_i is neither an ancestor nor a descendant of B_j in G.

To give a concrete example, we introduce a second stored procedure, named `Deposit`, that deposits an amount to some person's bank account, as shown in Figure 4. The local dependency graphs for these two procedures as well as the global dependency graph

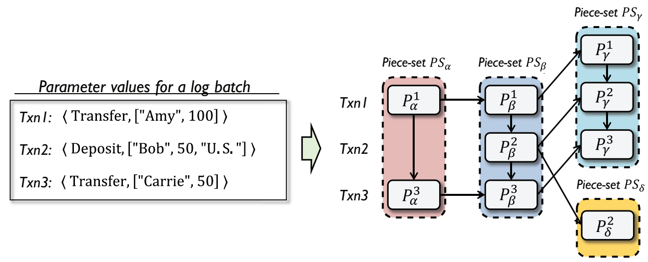


Figure 6: Execution schedule for a log batch containing three transactions.

for them are shown in Figure 5. Observe that T_2 and D_1 are data-dependent slices residing in same block B_β. For simplicity, the dependency from B_α and B_γ is omitted in the figure as it can be inferred from both the dependency from B_α to B_β as well as the dependency from B_β to B_γ.

4.2 Recovery Execution Schedules

In this section, we explain how PACMAN could parallelize recovery from the log batches by exploiting the global dependency graph derived from static analysis.

During recovery, PACMAN generates an execution schedule for each log batch using the global dependency graph (GDG). We explain this process using the example illustrated in Figure 6 for a simple log batch containing three transactions: transactions `Txn1` and `Txn3` invoke the *Transfer* procedure, while transaction `Txn2` invokes the *Deposit* procedure.

Recall that PACMAN applies a static analysis to segment each stored procedure into multiple slices to facilitate parallel execution. Thus, each invocation of a stored procedure is actually executed in the form of a set of *transaction pieces* (or pieces for short) corresponding to the slices for that procedure. The execution schedule shown in Figure 6 for the three transactions is actually a directed acyclic graph of the transaction pieces that are instantiated from the GDG in Figure 5.

Each transaction piece is denoted by P_b^t, where t identifies the transaction order in the log batch and b identifies the block identifier in the GDG. For instance, `Txn2` is instantiated into three pieces: P_β^2, P_γ^2 and P_δ^2. The directed edges among these pieces for a transaction reflect the dependencies of their corresponding slices from the GDG. The pieces from all three transactions are organized into four piece-sets (PS_α, PS_β, PS_γ, and PS_δ). The pieces within the same piece-set correspond to slices in the same GDG block, and these pieces are ordered (as indicated by the directed edges between them) following the transaction order in the batch log.

We say that a piece p is dependent on another piece p' (or p' is a dependent piece of p) in an execution schedule ES if p is reachable from p' in ES.

Given an execution schedule for a log batch, the replay of the schedule during recovery must respect the dependencies among the pieces. Specifically, a piece can be executed if all its dependent pieces have completed executions. For example, for the execution schedule in Figure 6, the piece P_γ^2 can be executed once its dependents (P_γ^1 and P_β^2) have completed executions, and the piece P_γ^2 could be executed in parallel with both P_δ^2 and P_β^3.

4.2.1 *Efficient Coarse-Grained Parallelism*

While the above approach enables each log batch to be replayed with some degree of fine-grained parallelism during recovery, it could incur expensive coordination overhead when concurrent execution is enabled. This is because any transaction piece will need to initiate the execution of possibly multiple child pieces, and such initiation essentially requires accessing synchronization primitives for notifying concurrent threads. As an example, the completion of piece P_β^1 will result in two primitive accesses for the initiation of P_β^2 and P_γ^1, while piece P_β^2 will lead to three coordination requests.

To reduce the coordination overhead involved in activating many piece executions, PACMAN instead handles the coordination at the level of piece-sets by executing each piece-set with a single thread[2]. The completion of a piece-set is accompanied with one or more coordination requests, each of which initiates the execution of another piece-set. By coordinating the executions at the granularity of piece-sets, the execution output generated by each piece from PS_α are delivered together, subsequently activating the execution of PS_β with only a single coordination request. For a large batch of transactions, this approach can improve the system performance significantly, as we shall see in our extensive experimental study.

4.3 Dynamic Analysis

In this section, we explain how PACMAN could further optimize the recovery process with a dynamic analysis of the execution schedules[3]. Specifically, the performance improvement comes from two techniques. First, by exploiting the availability of the runtime procedure parameter values, PACMAN enables further intra-batch parallel executions. Second, by applying a pipelined execution optimization, PACMAN enables inter-batch parallel executions where different log batches are replayed in parallel.

4.3.1 Fine-Grained Intra-Batch Parallelism

Based on the discussion in Section 4.2.1, the transaction pieces within each piece-set will be executed following the transaction order in the log batch, and the operations within each piece will also be executed serially. As an example, consider the execution of the the piece-set PS_β in Figure 6, where the three pieces in it are instantiated from the procedure slices T_2 and D_1 as shown in Figure 7. The transaction pieces in PS_β will be executed serially in the order P_β^1, P_β^2, and P_β^3; and within a piece, for instance piece P_β^1 (which corresponds to slice T_2), the four operations inside will also be executed serially. Such conservative serial executions are indeed inevitable if we are relying solely on the static analysis of the stored procedures.

However, given that the procedure/piece parameter values are actually available at runtime from both the log entries as well as the from those piece-sets that have already been replayed, PACMAN exploits such runtime information to further parallelize the execution of piece-sets. Specifically, since the read and write sets of each transaction piece could be identified from the piece's input arguments at replay time, two operations in the same piece-set can be executed in parallel if they fall into different *key spaces* (i.e., the two operations are not accessing the same tuple) and there is no flow dependency between these operations. Similarly, two pieces in a piece-set can be executed in parallel if their operations are not accessing any common tuple and there is no flow dependency between the piece-sets.

Continuing with our example of the execution of the piece-set PS_β in Figure 7, the tuples accessed by each operation in these pieces can be identified by checking the input arguments. For ex-

[2]As we shall see in Section 4.3.1, PACMAN can parallelize the execution of a piece-set after extracting fine-grained intra-batch parallelism.

[3] The analysis is dynamic in the sense that it utilizes the runtime log record information in contrast to the static predefined stored procedure information used by static analysis.

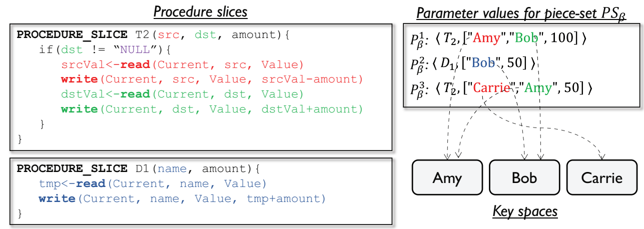


Figure 7: Execution of piece-set PS_β containing three transaction pieces.

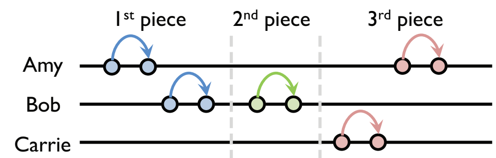


Figure 8: Exploiting runtime information to identify accessed tuples in the execution of piece-set PS_β. The flow dependencies (depicted by curved arrows) between operations are known from static analysis.

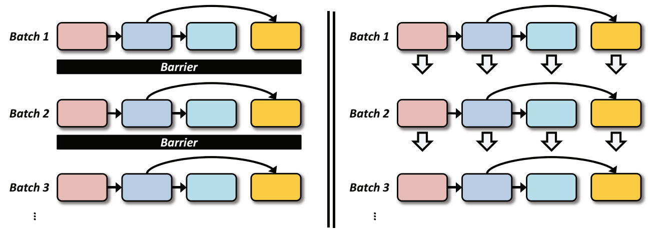
ample, the argument `Amy` in the piece P_β^1 identifies the accessed tuple for the first two operations listed in slice T_2, while `Bob` identifies the accessed tuple for the remaining two operations in T_2. Similarly, observe that the tuple being accessed by the operations in P_β^2 is determined by the argument `Bob`; and the tuples being accessed by the operations in P_β^3 are determined by the arguments `Amy` and `Carrie`. Figure 8 illustrates the tuples accessed by the operations in the execution of PS_β; the flow dependencies shown are known from the static analysis. Clearly, since the two tuples (with keys `Amy` and `Bob`) accessed by the two pairs of operations in P_β^1 (corresponding to slice T_2) are distinct and there is no flow dependency between these pairs of operations, these two pairs of operations can be safely executed in parallel without any coordination. By a similar argument, the two pieces P_β^2 and P_β^3 can be executed in parallel once the piece P_β^1 has completed execution. It is important that the execution of P_β^1 be completed before starting P_β^2 and P_β^3 as the operations in P_β^1 conflict with those in each of P_β^2 and P_β^3.

Observe that the flow dependencies shown for the execution of PS_β in Figure 8 are due to what have been referred to as *read-modify-write* access patterns [40]. This access pattern involves two operations: the first operation reads a row and the second operation updates the row read by the first operation. As illustrated by the above discussion, if the read-modify-write patterns access different records, then the flow dependencies among these operations would not hinder their parallel executions.

Yet another commonly seen access pattern is what we call *foreign-key* access pattern. In a foreign-key pattern, an operation reads a row r_1 from a table and then writes a related row r_2 in another table, where r_1 (or r_2) has a foreign key that refers to r_2 (or r_1). Line 2 and Lines 4-5 in Figure 2 share this pattern[4], as the specific rows to be accessed in tables `Customer` and `Current` can be determined by `src`, meaning that these operations actually belong to the same key space.

Both the read-modify-write and foreign-key access patterns are

[4] This example is actually more sophisticated because Line 2 and Lines 4-5 fall into different slices. But we cannot prevent cases where operations in the same slice are flow-dependent.



(a) Synchronous execution. (b) Pipelined execution.

Figure 9: Synchronous execution vs pipelined execution for three log batches. Each rectangle represents a piece-set in an execution schedule.

common in real-world applications. In our analysis of fifteen well-known OLTP benchmarks [2], we observe that all the existing flow dependencies in these benchmarks are due to these two patterns. Moreover, our extensive experimental studies have also confirmed this observation. The prevalence of these two patterns indicates the potential for parallel operation executions.

4.3.2 Inter-Batch Parallelism

So far, our focus has been on intra-batch parallelism to optimize the performance of executing an individual log batch schedule. However, a DBMS usually need to recover tens of thousands of log batches during the entire log recovery phase, as it is difficult to reload tens- or even hundreds-of-gigabyte of log data into DRAM at once. By extracting purely intra-batch parallelism, the DBMS has to execute log batches serially one after another, and we refer to this execution mode as *synchronous execution*. As illustrated by the simple example in Figure 9(a) showing the execution of three log batches (which happen to have the same execution schedules), such a serial execution requires synchronization barriers to coordinate the thread executions. To enable inter-batch parallelism, PACMAN supports a *pipelined execution* model that enables a log batch to begin being replayed without having to wait for the replay of the preceding log batch to be entirely completed. Specifically, a piece-set P associated with a log batch B could start execution once its dependent piece-sets (w.r.t. B) and any piece-set in the same block as P associated with its preceding log batch have completed.

4.4 Recovery Runtime

PACMAN re-executes transactions as a pipeline of order-preserving data-flows, which is facilitated by the combination of the static and dynamic analyses described above. Given the global dependency graph (GDG) generated at static-analysis stage, PACMAN estimates the workload distributions over the piece-sets of each procedure block by counting the number of pieces at log file reloading time. Based on this distribution, PACMAN assigns a fixed number of CPU cores in the machine to each block. When a log batch is reloaded to main memory, PACMAN generates an execution schedule based on the GDG, where the instantiated piece-sets are one-to-one mapped to the blocks in the GDG (see Section 4.2). PACMAN thus can process each piece-set using the cores assigned to the corresponding block, hence extracting coarse-grained recovery parallelism. To enable finer-grained parallelism for recovery, PACMAN further dispatches operations inside a piece-set into different cores by exploiting the availability of the runtime parameter values (see Section 4.3.1). This scheme allows PACMAN to fully utilize computation resources for processing a single log batch. PACMAN also exploits parallelisms across multiple log batches, and this is achieved by pipelining the processing of different execution schedules (Section 4.3.2).

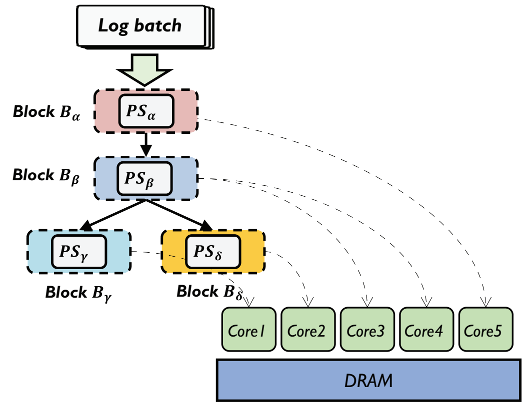


Figure 10: Recovery runtime of PACMAN. The workload distribution over the piece-sets of each block (B_α, B_β, B_γ, and B_δ) in the GDG is 20%, 40%, 20%, and 20%.

Figure 10 gives a concrete example of how PACMAN performs database recovery for an application containing the `Transfer` and `Deposit` procedures. By estimating the workload distribution at log file reloading time, PACMAN assigns different number of cores to each block. When processing a log batch, PACMAN constructs an execution schedule and splits the log batch into four piece-sets, namely PS_α, PS_β, PS_γ, and PS_δ. For a certain piece-set, for instance PS_β, PACMAN processes it using the two cores assigned to block B_β. The operations within PS_β are dispatched to these two cores using dynamic analysis. PACMAN finishes processing this log batch once all the four piece-sets have been recovered. PACMAN's pipelined execution model further allows a log batch to be processed even if its preceding log batch is still under execution.

4.5 Ad-Hoc Transactions

PACMAN is designed for main-memory DBMSs that adopt command logging scheme for preserving database durability. A known drawback of this logging scheme is that the execution behavior of a transaction containing nondeterministic operations (e.g., `SELECT * FROM FOO LIMIT 10`) cannot be precisely captured [24]. Also, command logging does not naturally support transactions that are not issued from stored procedures. We refer to these transactions as ad-hoc transactions. To support these transactions, a DBMS must additionally support conventional tuple-level logical logging to record every row-level modification of a transaction [24].

The co-existence of both transaction-level and tuple-level logs calls for a unified re-execution model that ensures the generality of our proposed recovery mechanism. PACMAN solves this problem by treating the replay of a transaction that is persisted using logical logging as the processing of a write-only transaction. With the full knowledge of a transaction's write set, high degree of parallelism is easily extracted, as each write operation can be dispatched to the corresponding piece-subset of a certain block through dynamic analysis described in Section 4.3. Note that the replay of the tuple-level logs produced by ad-hoc transactions must still follow the strict re-execution order captured in the log batches. As such, PACMAN's solution enables the unification of recovery for transaction-level logging and tuple-level logging.

One extreme case for PACMAN is that all the transactions processed by the DBMS are ad-hoc transactions. In this case, PACMAN works essentially the same as a pure logical log recovery scheme. However, compared to existing solution [48], PACMAN does not need to acquire any latch during the log replay, and hence, when multiple threads are utilized, it yields much higher performance than existing tuple-level log recovery schemes that employ latches during recovery. This is confirmed by the experiment results shown in Section 6.

5. DISCUSSION

While PACMAN provides performance benefits for transaction-level logging-and-recovery mechanisms, it has several limitations.

Foremost is that PACMAN relies on the use of stored procedures. Despite the fact that most DBMSs provide support for stored procedures, many application developers still prefer using dynamic SQL to query databases for reducing the coding complexity. Although this limitation can restrict the use of PACMAN, an increasing number of performance-critical applications such as on-line trading and Internet-of-Things (IoT) processing have already adopted stored procedures to avoid the round-trip communication cost. PACMAN is applicable for these scenarios without any modifications.

Second, PACMAN's static analysis requires the stored procedures to be deterministic queries with read and write sets that can be easily computed. Furthermore, it remains a challenging problem for PACMAN to support nested transactions or transactions containing complex logic. As mentioned in Section 4.5, to address this problem, a DBMS has to resort to conventional tuple-level logging for persisting every row-level modification of a transaction.

6. EVALUATION

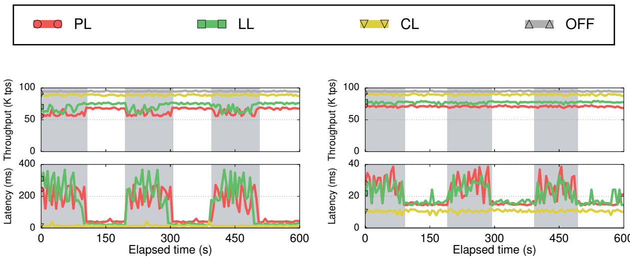
In this section, we evaluate the effectiveness of PACMAN, by seeking to answer the following key questions:

1. Does PACMAN incur a significant logging overhead for transaction processing?
2. Can PACMAN achieve a high degree of parallelism during failure recovery?
3. How does each proposed mechanism contribute to the performance of PACMAN?

We implemented PACMAN in Peloton, a fully fledged main-memory DBMS optimized for high performance transaction processing. Peloton uses a B-tree style data structure for database indexes, and it adopts multi-versioning for higher level of concurrency [42]. In addition to PACMAN, we also implemented the state-of-the-art tuple-level (both physical and logical) and transaction-level logging-and-recovery schemes in Peloton. In our implementation, we have optimized the tuple-level logging-and-recovery schemes by leveraging multi-versioning. However, PACMAN does not exploit any characteristics of multi-versioning, as the design of PACMAN makes no assumption about the data layout, and it is general enough to be directly applicable for single-version DBMSs. We present the implementation details in Appendix A.

We performed all the experiments on a single machine running Ubuntu 14.04 with four 10-core Intel Xeon Processor E7-4820 clocked at 1.9 GHz, yielding a total of 40 physical cores. Each core owns a private 32 KB L1 cache and a private 256 KB L2 cache. Every 10 cores share a 25 MB L3 cache and a 32 GB local DRAM. The machine has two 512 GB SSDs with maximum sequential read and sequential write throughput of 550 and 520 MB/s respectively.

Throughout our experiments, we evaluated the DBMS performance using two well-known benchmarks [11], namely, TPC-C and Smallbank. The global dependency graph for TPC-C is presented in Appendix C. Except for Figure 11a, which reports the logging performance using a single SSD, all the other experiment results presented in this section adopt two SSDs, each assigned with a single logging thread and a single checkpointing thread [48].



(a) With one SSD. (b) With two SSDs.

Figure 11: Throughput and latency comparisons during transaction processing. PL, LL, and CL stand for physical logging, logical logging, and command logging, respectively.

	Throughput (K tps)			Log size (GB/min)			Log size ratio	
	PL	LL	CL	PL	LL	CL	PL/CL	LL/CL
TPC-C	71	74	93	13.7	12.9	1.2	11.4	10.8
Smallbank	503	564	595	1.6	1.2	1.3	1.23	0.92

Table 1: Log size comparison.

6.1 Logging

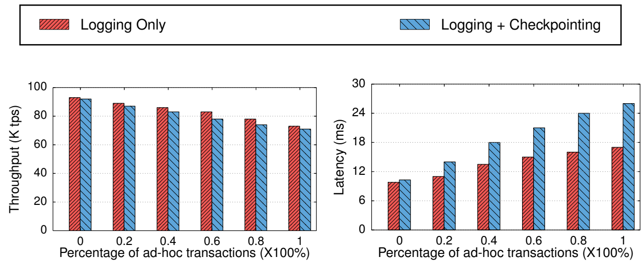
In this section, we investigate how different logging schemes influence the performance of transaction processing. We first measure the runtime overhead incurred by different logging schemes, and then evaluate how ad-hoc transactions affect the performance of transaction-level logging scheme. Our experiment results demonstrate the effectiveness of the transaction-level logging scheme.

6.1.1 *Logging Overhead*

We begin our experiments by evaluating the runtime overhead incurred by each logging scheme when processing transactions in the TPC-C benchmark. Similar trends were observed for the Smallbank benchmark. We set the number of warehouses to 200 and the database size is approximately 20 GB[5]. Due to the memory limit of our experiment machine, we disabled the insert operations in the original benchmark so that the database size will not grow without bound. We configure Peloton to use 32 threads for transaction executions, 2 threads for logging, and 2 threads for checkpointing. We further configure Peloton to perform checkpointing every 200 seconds.

Figure 11 shows the throughput and the latency of the DBMS for the TPC-C benchmark a 10-minute duration. Intervals during which the checkpointing threads are running are shown in gray. With both logging and checkpointing disabled (denoted as OFF), the DBMS achieves a stable transaction processing throughput of around 95 K tps. However, the first 100-second trace in Figure 11a depicts that, using one SSD, the throughput of the DBMS can drop by $\sim$25% when both checkpointing and tuple-level logging, namely physical logging (denoted as PL) and logical logging (denoted as LL), are enabled. When the DBMS finished performing checkpointing, the throughput rises to around 76 K tps (see the throughput of LL from 100 to 200 seconds), but this number is still

[5] Note that the database size measures only the storage space for tuples; the total storage space occupied by the tuples and other auxiliary structures (e.g., indexes, lock tables) is about 70 GB.



(a) Throughput. (b) Latency.

Figure 12: Logging with ad-hoc transactions.

20% lower than the case where recovery schemes in the DBMS are fully disabled. Compared to tuple-level logging schemes, the runtime overhead incurred by transaction-level logging, or command logging (denoted as CL), is negligible. Specifically, the throughput reduction caused by CL is under 6% even when checkpointing threads were running.

Tuple-level logging schemes also caused a significant increase in transaction latency. As Figure 11a shows, there are high latency spikes when checkpointing threads were running. In the worst case, the latency can go beyond 300 milliseconds, which is intolerable for modern OLTP applications. To mitigate this problem, a practical solution is to equip the machine with more storage devices.

Figure 11b shows the transaction throughput and latency achieved when persisting checkpoints and logs to two separate SSDs. The result shows that adding more SSDs can effectively minimize the drop in throughput and significantly reduce the latency of tuple-level logging. However, tuple-level logging still incurs $\sim$20% of throughput degradation, and its latency is at least twice higher than that of transaction-level logging. These results demonstrate while the performance of tuple-level logging could be improved with additional storage devices, transaction-level logging still outperforms tuple-level logging.

The major factor that causes the results shown above is that tuple-level logging schemes usually generate much more log records than transaction-level logging, and the SSD bandwidth can be easily saturated when supporting high throughput transaction processing. As shown in Table 1, the log size generated by logical logging in the TPC-C benchmark can be 10.8X larger than that generated by command logging. Physical logging yields an even larger log size because it must record the locations of the old and new versions of every modified tuple. In the Smallbank benchmark, while the log size generated by the different logging schemes are similar, command logging still yields comparatively better performance than the other schemes. This is because log data serialization in physical and logical logging schemes requires the DBMS to iterate a transaction's write set and serialize every attribute of each modified tuple into contiguous memory space. This process leads to higher overhead than that in command logging. Appendix D presents additional analysis of the impact of SSD bandwidth and `fsync` operations on the performance of the different logging schemes.

6.1.2 Ad-Hoc Transactions

As discussed in Section 4.5, the logging of ad-hoc transactions incurs additional overhead as the DBMS needs to log row-level modifications. In this section, we evaluate the logging overhead for ad-hoc transactions using the TPC-C benchmark. Similar trends were observed for Smallbank benchmark. In our experiment, we randomly tag some transactions as ad-hoc transactions. As shown in Figure 12a, the transaction throughput achieved by the DBMS drops almost linearly with the increase of the percentage of ad-hoc transactions. Figure 12b further shows that the transaction latency increases significantly with the increase in percentage of ad-hoc transactions especially when checkpointing is performed along with logging. When 100% of the transactions are ad-hoc, the performance degrades significantly as the DBMS essentially ends up performing pure logical logging. Based on these results, we confirm that the overhead incurred by command logging is no higher than that incurred by logical logging.

6.2 Recovery

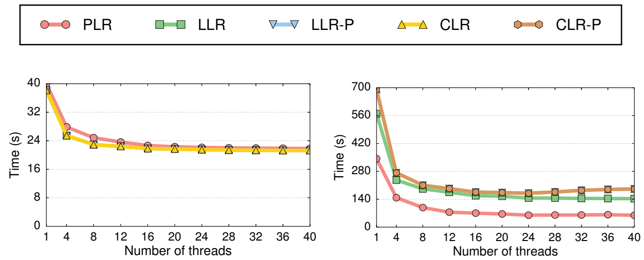
This section evaluates the performance of PACMAN for database recovery. Our evaluation covers the following schemes:

- **PLR:** This is the physical log recovery scheme that is widely implemented in conventional disk-based DBMSs. It first reloads and replays the logs to restore tables with committed updates using multiple threads. After that, it rebuilds all the indexes in parallel. It adopts last-writer-wins rule to reduce log recovery time. A recovery thread must first acquire a latch on any tuple that is to be modified. The recovered database state is multi-versioned.
- **LLR:** This is the state-of-the-art logical log recovery scheme proposed in SiloR [48]. It reconstructs the lost database records and indexes at the same time. While the original scheme was designed for single-version DBMSs, we have optimized this scheme by exploiting multi-versioning to enable two recovery threads to restore different versions of the same tuple in parallel. To ensure that all new tuple versions are appended correctly to the appropriate version chains, latches are acquired by the recovery threads on the tuples being modified. The recovered database state is multi-versioned.
- **LLR-P:** This is the parallel logical log recovery scheme adapted from PACMAN (see Section 4.5). It treats the restoration of each transaction log entry as the replay of a write-only transaction. During the log replay, it shuffles the write operations according to the table ID and primary key. After that, it reinstalls these operations in a latch-free manner. The recovered database state is single-versioned.
- **CLR:** This is the conventional approach for command log recovery. It reloads log files into memory in parallel and then re-executes the lost committed transactions in sequence using a single thread. The recovered database state is single-versioned.
- **CLR-P:** This is the parallel command log recovery scheme (PACMAN) described in this paper. The recovered database state is single-versioned.

The entire database recovery process operates in two stages: (1) checkpoint recovery, which restores the database to the transactionally-consistent state at the last checkpoint; and (2) log recovery, which reinstalls the effects made by all the lost committed transactions. We study these two stages separately, and then evaluate the overall performance of the entire database recovery process. Finally, we study the effect of ad-hoc transactions.

6.2.1 Checkpoint Recovery

We first examine the performance of each scheme's checkpoint recovery stage. We use the TPC-C benchmark and require the



(a) Pure checkpoint file reloading. (b) Overall time duration.

Figure 13: Performance of checkpoint recovery.

DBMS to recover a 20 GB database state. Figure 13a compares the checkpoint file reloading time of each recovery scheme. The result shows that different recovery schemes require a similar time duration for reloading checkpoint files from the underlying storage, and the reloading speed can easily reach the peak bandwidth of the two underlying SSDs, which is $\sim$1 GB/s. However, the results in Figure 13b indicate that PLR's checkpointing scheme requires much less time for completing the entire checkpoint recovery phase. This is because this scheme only restores the database records during checkpoint recovery, and the reconstruction of all the database indexes is performed during the subsequent log recovery phase. All the other checkpointing schemes, however, must perform on-line index reconstruction, as their subsequent log recovery phase needs to use the indexes for tuple retrievals. LLR's checkpoint recovery scheme also perform slightly faster than the rest ones, as it can leverage multi-versioning to increase the recovery concurrency.

6.2.2 *Log Recovery*

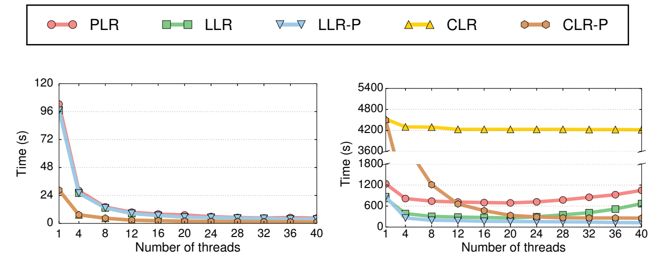
We now compare each scheme's log recovery stage using the TPC-C benchmark. The recovery process was triggered by crashing the DBMS after the benchmark has been executed for 5 minutes.

Figure 14a shows the recovery time of each log recovery scheme. Compared to the tuple-level log recovery schemes (i.e., PLR, LLR, and LLR-P), the transaction-level log recovery schemes (i.e., CLR and CLR-P) require much less time for log reloading. This is because transaction-level logging can generate much smaller log files compared to tuple-level logging, especially when processing write-intensive workloads (like TPC-C).

Figure 14b also demonstrates the significant performance improvement of CLR-P over CLR. As CLR utilizes only a single thread for log replay, CLR took over 4,200 seconds (70 minutes) to complete the log recovery. In contrast, by utilizing multiple threads for recovery, our proposed CLR-P was able to outperform CLR by a factor of 18. Observe that the performance of CLR-P improves significantly with the number of recovery threads. As CLR-P already schedules the transaction re-execution order (using both static and dynamic analyses), CLR-P does not require latching during recovery and therefore is not hampered by the latch synchronization overhead inherent in CLR.

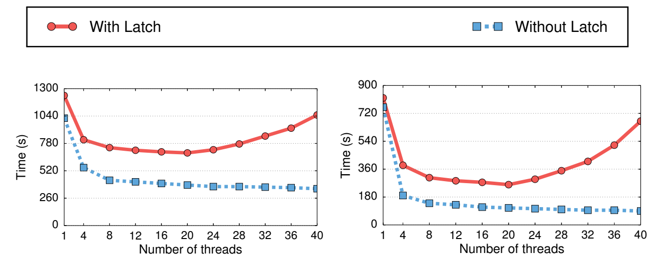
Observe that for both PLR and LLR, their recovery times improve with the number of recovery threads up to 20 threads and beyond that point, their recovery times increase with the number of recovery threads. This is because the recovery threads in both PLR and LLR (which follow SiloR's design) require latches on tuples to be modified for recovery correctness, and the synchronization overhead of using latches start to degrade the overall performance beyond 20 recovery threads.

To try to quantify the latching overhead incurred by PLR and



(a) Pure log file reloading. (b) Overall time duration.

Figure 14: Performance of log recovery.



(a) PLR. (b) LLR.

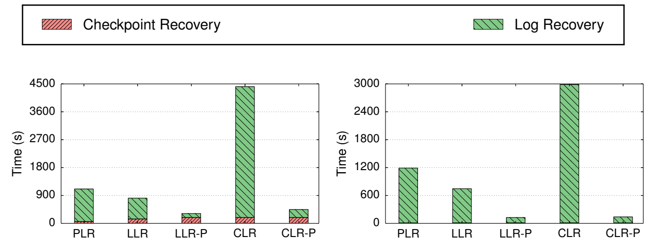
Figure 15: Latching Bottleneck in tuple-level log recovery schemes.

LLR, we removed the latch acquisition operations in both of these recovery schemes and then measured their recovery performance. Of course, without the use of latches, both PLR and LLR could produce inconsistent database states after recovery; however, the attained performance measurements would essentially indicate the peak performance achievable by PLR and LLR. As shown in Figure 15, with the latch acquisition disabled, the recovery times of both PLR and LLR drop significantly with the increase in the number of recovery threads. Observe that the time reduction after 12 threads is not quite significant. This is because (1) the scalability of the log reloading phase is bounded by the maximum read throughput of the underlying SSD storage; and (2) the scalability of the log replay phase is also constrained by the performance of the concurrent database indexes. With 20 recovery threads, the recovery times of PLR and LLR were reduced to the minimum at around 750 and 270 seconds respectively. However, scaling these two schemes towards 40 threads significantly increases the recovery time to over 1000 and 700 seconds, respectively. These results show the inefficiency of the state-of-the-art tuple-level log recovery schemes.

6.2.3 *Overall Performance*

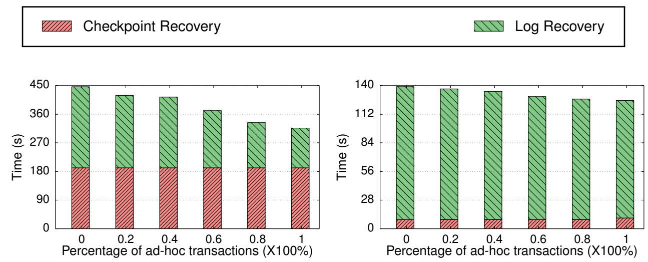
This section evaluates the overall performance of the recovery schemes using 40 recovery threads. As before, the recovery schemes were triggered after 5 minutes of transaction processing.

As shown in Figure 16, CLR performed the worst in both benchmarks as CLR cannot leverage multi-threading for reducing log recovery time. Our proposed scheme, LLR-P, achieved the best performance. This is due to two main reasons. First, unlike CLR, LLR-P is able to exploit multiple recovery threads for efficient recovery. Second, LLR-P schedules the transaction re-execution order beforehand and it does not require any latching thereby avoiding the synchronization overhead that is incurred by both PLR and LLR schemes. We note that CLR-P consumes more time than LLR-P for recovering the database. This is because CLR-P has



(a) TPC-C. (b) Smallbank.

Figure 16: Overall performance of database recovery.



(a) TPC-C. (b) Smallbank.

Figure 17: Database recovery with ad-hoc transactions.

to re-execute all the operations (including both read and write) in a transaction, whereas LLR-P only reinstalls modifications recorded in the log files. For all the compared schemes, the checkpoint recovery time is almost negligible, as this phase is easily parallelized.

6.2.4 Ad-Hoc Transactions

We further measure how the presence of ad-hoc transactions influence PACMAN's performance in database recovery. We use the same configurations as the previous experiments, and mix the workload with certain percentage of ad-hoc transactions. Figure 17 shows the results. By varying the percentage of ad-hoc transactions from 0% to 100%, the recovery time of PACMAN drops smoothly. When the percentage of ad-hoc transactions is increased to 100%, this result essentially show the performance of LLR-P. As recovering command logs requires the DBMS to perform all the read operations in the stored procedure, it takes more time compared to pure logical log recovery. This results confirmed the efficiency of PACMAN's support of ad-hoc transactions.

The experiment results reported in this section confirmed that PACMAN requires a much lower recovery time for restoring lost database states compared with the state-of-the-art recovery schemes, even in the existence of ad-hoc transactions.

6.3 Performance Analysis

In this section, we analyze the effectiveness of each of the proposed mechanisms in PACMAN using the TPC-C benchmark. In particular, we measure the recovery performance achieved by PACMAN's static analysis and dynamic analysis, and then investigate the potential performance bottlenecks in PACMAN.

The results reported in this section are based on running the benchmark for a duration of five minutes and then triggering a database crash to start the recovery process. As both static and dynamic analyses are designed for log recovery, we omit checkpoint recovery in this section's experiments.

6.3.1 Static Analysis

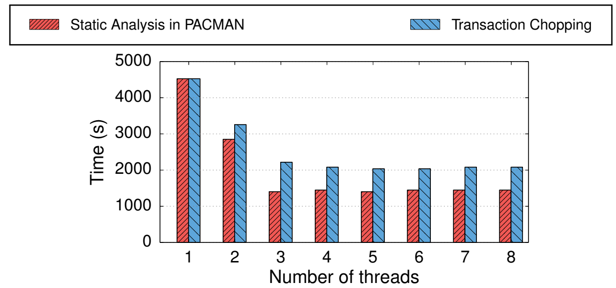


Figure 18: Effectiveness of static analysis.

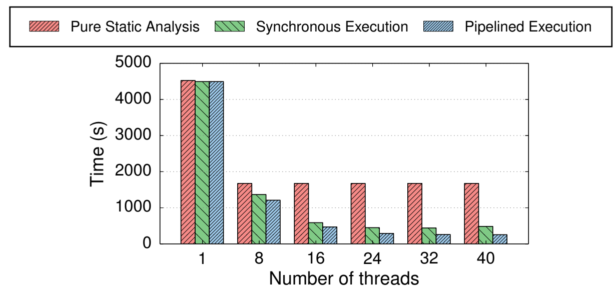


Figure 19: Effectiveness of dynamic analysis.

As the static analysis in PACMAN relies on decomposing stored procedures into slices to enable execution parallelism, we compare the effectiveness of PACMAN's decomposition technique against a baseline technique that is adapted from the well-known transaction chopping technique [36]. A qualitative comparison of these two techniques is given in Section 7.

Figure 18 compares the log recovery performance achieved by PACMAN's static analysis and the transaction chopping-based scheme. For this experiment, the dynamic analysis phase was disabled to focus on the comparison between the two competing static analysis techniques. The results show that, as the number of threads increases from 1 to 3, the recovery time achieved by PACMAN's static analysis decreases from 4500 seconds to ∼2000 seconds. But beyond this point, the recovery time stops decreasing and there is no further performance gain brought from the increased thread count. This is because PACMAN's static analysis extracts only coarse-grained parallelism for log recovery, and dynamic analysis needs to be incorporated to fully exploit the multi-thread execution. The same figure also shows the recovery time required by transaction chopping is always longer than that required by PACMAN's static analysis. This is because the decomposition obtained from PACMAN is finer-grained than that from transaction chopping.

6.3.2 Dynamic Analysis

This section examines the effectiveness of the dynamic analysis in PACMAN. We analyze the benefits of intra- and inter-batch parallelism by comparing three techniques: (1) using only static analysis techniques (without applying any techniques from dynamic analysis), (2) using techniques from both static analysis and intra-batch parallelism techniques (i.e., synchronous execution), and (3) using all the techniques from static and dynamic analyses (i.e., pipelined execution). Figure 19 shows that, by using synchronous execution, PACMAN yields over 4 times lower recovery time compared to that achieved by pure static analysis with 40 threads enabled. The performance is further improved by exploiting inter-batch parallelism. Specifically, with pipelined execution, the recovery time of PAC-

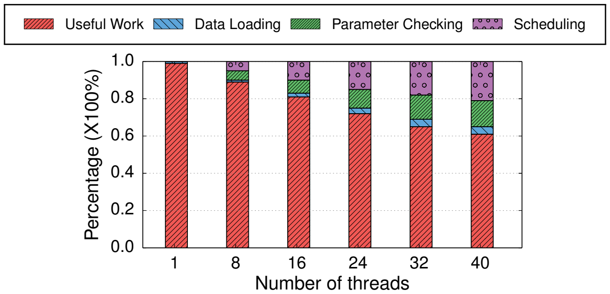


Figure 20: Log recovery time breakdown.

MAN drops to less than 300 seconds when utilizing 40 threads. This result confirms that both the intra- and inter-batch parallelism extracted in PACMAN can help improve the system scalability and hence reduce recovery time.

6.3.3 Time Breakdown

Having understood how each of the proposed mechanisms contributes to the system performance, we further investigate the performance bottleneck of PACMAN. The bottleneck can potentially come from three sources. First, the DBMS needs to load the log files from the underlying storage and deserialize the logs to the main-memory data structures. Second, the dynamic analysis in PACMAN requires that the parameter values in each log batch be analyzed for deriving intra-batch parallelism, possibly blocking the subsequent tasks. Third, the scheduling of multiple threads requires each thread to access a centralized data structure, potentially resulting in intensive data races. We break down the recovery time of PACMAN and show the result in Figure 20. By scaling PACMAN to 40 threads, thread scheduling becomes the major bottleneck, occupying around 30% of the total recovery time. In contrast, log data loading and dynamic analysis are very lightweight, and these two processes do not lead to high overhead. Observing the performance bottleneck in PACMAN, we argue that employing a better scheduling mechanism can help further optimize the performance of database recovery.

7. RELATED WORK

Main-memory DBMSs have been well studied by the research community for over two decades [9, 14, 17, 18, 40, 44]. Database recovery for such DBMSs use a combination of checkpointing and logging mechanisms. While there have been many recent approaches on improving the performance of checkpointing [6, 22, 33, 34], several previous works [24, 48], as well as our study in this paper, have shown that log recovery is the major bottleneck for database recovery.

Log-based recovery techniques face a performance trade-off between transaction processing and failure recovery. While tuple-level logging [25] offers faster recovery than transaction-level logging [23, 24], the latter incurs lower overhead during normal transaction processing. Existing works largely focused on optimizing tuple-level logging mechanisms with techniques such as log compression [9, 21] and using hardware support [16, 29, 41, 48]. A recent work by Yao et al. [46] investigated the recovery costs between transaction-level and tuple-level logging for distributed in-memory DBMSs. As a significant departure from existing works, our work on PACMAN focuses on achieving high performance in both the logging and recovery processes for the transaction-level logging approach.

The idea behind PACMAN is inspired a series of recent works that leverage transaction analysis for advanced performance. For example, Doppel [27] execute commutative operations in parallel for higher transaction-processing throughput. Yan et al. [45] extracted data dependencies within transactions to improve transaction processing performance under high-contention workloads. Wu et al. [43] analyzed dependencies within each transaction to scale conventional optimistic concurrency control on multicores. A well-known technique in this area is transaction chopping [36], which tries to increase the concurrency for a given workload of transactions. By analyzing the conflicting operations among the transactions in the workload, each transaction is decomposed into a set of smaller sub-transactions such that any strict two-phase locking execution of the collection of sub-transactions is a serializable execution (w.r.t. to the original workload of non-decomposed transactions). Several recent works have applied transaction chopping to optimize the processing of distributed transactions [26, 47].

Similar to the use of conflicting operations for decomposing transactions in transaction chopping, the static analysis in PACMAN uses flow dependencies to decompose stored procedures into slices. However, a key difference between these techniques is that they are developed for different objectives that have different constraints. The goal of transaction decompositions in PACMAN is to parallelize the replay of committed transactions during database recovery, and thus the execution order of the decomposed transaction pieces is chosen to maximize execution parallelism while respecting the ordering constraints from the flow dependencies among the transaction operations and that from the transactions in the recovery log. In contrast, transaction chopping is designed to maximize concurrency during normal transaction executions and its decomposition needs to satisfy a different and stronger property that any strict 2PL execution of the decomposed sub-transactions is serializable. Consequently, the granularity of the decompositions from transaction chopping are coarser than those from PACMAN.

The techniques used in our dynamic analysis share some similarities with concurrency control techniques in that they both aim to find opportunities for inter-transaction parallelism. However, a key difference between these techniques is the context in which they operate. In the context of PACMAN for database recovery, the set of committed transactions to be replayed are known before the start of recovery and the input parameter values for the transactions are also known from the recovery log. Consequently, PACMAN is able to exploit more information to maximize execution parallelism. In contrast, conventional concurrency control techniques are applied in a more dynamic context where the order of incoming transaction operations is not known apriori and thus the parallelism opportunities are more limited.

8. CONCLUSION

We have developed PACMAN, a database recovery mechanism that achieves speedy failure recovery without introducing any costly overhead to the transaction processing. By leveraging a combination of static and dynamic analyses, PACMAN exploits fine-grained parallelism for replaying logs generated by coarse-grained transaction-level logging. By performing extensive performance studies on a 40-core machine, we confirmed that PACMAN can significantly reduce the database recovery time compared to the state-of-the-art recovery schemes.

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9. REFERENCES

[1] MySQL. http://www.mysql.com.

[2] OLTPBench. http://oltpbenchmark.com/.

[3] Oracle. http://www.oracle.com.

[4] F. E. Allen. Control Flow Analysis. In *ACM SIGPLAN Notices*, 1970.

[5] T. M. Austin and G. S. Sohi. Dynamic Dependency Analysis of Ordinary Programs. In *ISCA*, 1992.

[6] T. Cao, M. Vaz Salles, B. Sowell, Y. Yue, A. Demers, J. Gehrke, and W. White. Fast Checkpoint Recovery Algorithms for Frequently Consistent Applications. In *SIGMOD*, 2011.

[7] A. Cheung, S. Madden, O. Arden, and A. C. Myers. Automatic Partitioning of Database Applications. In *VLDB*, 2012.

[8] J. C. Corbett, J. Dean, M. Epstein, A. Fikes, C. Frost, J. J. Furman, S. Ghemawat, A. Gubarev, C. Heiser, P. Hochschild, W. Hsieh, S. Kanthak, E. Kogan, H. Li, A. Lloyd, S. Melnik, D. Mwaura, D. Nagle, S. Quinlan, R. Rao, L. Rolig, Y. Saito, M. Szymaniak, C. Taylor, R. Wang, and D. Woodford. Spanner: Google's Globally-Distributed Database. In *OSDI*, 2012.

[9] D. J. DeWitt, R. H. Katz, F. Olken, L. D. Shapiro, M. R. Stonebraker, and D. A. Wood. Implementation Techniques for Main Memory Database Systems. In *SIGMOD*, 1984.

[10] C. Diaconu, C. Freedman, E. Ismert, P.-A. Larson, P. Mittal, R. Stonecipher, N. Verma, and M. Zwilling. Hekaton: SQL Server's Memory-Optimized OLTP Engine. In *SIGMOD*, 2013.

[11] D. E. Difallah, A. Pavlo, C. Curino, and P. Cudre-Mauroux. OLTP-Bench: An Extensible Testbed for Benchmarking Relational Databases. In *VLDB*, 2013.

[12] D. Gawlick and D. Kinkade. Varieties of Concurrency Control in IMS/VS Fast Path. *IEEE Data Eng. Bull.*, 8(2), 1985.

[13] J. Gray and A. Reuter. *Transaction Processing: Concepts and Techniques*. 1992.

[14] M. Grund, J. Krüger, H. Plattner, A. Zeier, P. Cudre-Mauroux, and S. Madden. HYRISE: A Main-Memory Hybrid Storage Engine. In *VLDB*, 2010.

[15] R. Johnson, I. Pandis, N. Hardavellas, A. Ailamaki, and B. Falsafi. Shore-MT: A Scalable Storage Manager for the Multicore Era. In *EDBT*, 2009.

[16] R. Johnson, I. Pandis, R. Stoica, M. Athanassoulis, and A. Ailamaki. Aether: A Scalable Approach to Logging. In *VLDB*, 2010.

[17] R. Kallman, H. Kimura, J. Natkins, A. Pavlo, A. Rasin, S. Zdonik, E. P. C. Jones, S. Madden, M. Stonebraker, Y. Zhang, J. Hugg, and D. J. Abadi. H-Store: A High-Performance, Distributed Main Memory Transaction Processing System. In *VLDB*, 2008.

[18] A. Kemper and T. Neumann. HyPer: A Hybrid OLTP & OLAP Main Memory Database System Based on Virtual Memory Snapshots. In *ICDE*, 2011.

[19] K. Kim, T. Wang, J. Ryan, and I. Pandis. ERMIA: Fast Memory-Optimized Database System for Heterogeneous Workloads. In *SIGMOD*, 2016.

[20] J. Lee, K. Kim, and S. K. Cha. Differential Logging: A Commutative and Associative Logging Scheme for Highly Parallel Main Memory Database. In *ICDE*, 2001.

[21] X. Li and M. H. Eich. Post-Crash Log Processing for Fuzzy Checkpointing Main Memory Databases. In *ICDE*, 1993.

[22] A.-P. Liedes and A. Wolski. Siren: A Memory-Conserving, Snapshot-Consistent Checkpoint Algorithm for In-Memory Databases. In *ICDE*, 2006.

[23] D. Lomet, K. Tzoumas, and M. Zwilling. Implementing Performance Competitive Logical Recovery. In *VLDB*, 2011.

[24] N. Malviya, A. Weisberg, S. Madden, and M. Stonebraker. Rethinking Main Memory OLTP Recovery. In *ICDE*, 2014.

[25] C. Mohan, D. Haderle, B. Lindsay, H. Pirahesh, and P. Schwarz. ARIES: A Transaction Recovery Method Supporting Fine-Granularity Locking and Partial Rollbacks Using Write-Ahead Logging. *TODS*, 17(1), 1992.

[26] S. Mu, Y. Cui, Y. Zhang, W. Lloyd, and J. Li. Extracting More Concurrency from Distributed Transactions. In *OSDI*, 2014.

[27] N. Narula, C. Cutler, E. Kohler, and R. Morris. Phase Reconciliation for Contended In-Memory Transactions. In *OSDI*, 2014.

[28] F. Nielson, H. R. Nielson, and C. Hankin. *Principles of Program Analysis*. 1999.

[29] D. Ongaro, S. M. Rumble, R. Stutsman, J. Ousterhout, and M. Rosenblum. Fast Crash Recovery in RAMCloud. In *SOSP*, 2011.

[30] I. Pandis, R. Johnson, N. Hardavellas, and A. Ailamaki. Data-Oriented Transaction Execution. In *VLDB*, 2010.

[31] A. Pavlo, G. Angulo, J. Arulraj, H. Lin, J. Lin, L. Ma, P. Menon, T. C. Mowry, M. Perron, I. Quah, S. Santurkar, A. Tomasic, S. Toor, D. Van Aken, Z. Wang, Y. Wu, R. Xian, and T. Zhang. Self-Driving Database Management Systems. In *CIDR*, 2017.

[32] K. Ramachandra, R. Guravannavar, and S. Sudarshan. Program Analysis and Transformation for Holistic Optimization of Database Applications. In *SOAP*, 2012.

[33] K. Ren, T. Diamond, D. J. Abadi, and A. Thomson. Low-Overhead Asynchronous Checkpointing in Main-Memory Database Systems. In *SIGMOD*, 2016.

[34] K. Salem and H. Garcia-Molina. Checkpointing Memory-Resident Databases. In *ICDE*, 1989.

[35] D. Schwalb, M. Faust, J. Wust, M. Grund, and H. Plattner. Efficient Transaction Processing for Hyrise in Mixed Workload Environments. In *IMDM*. 2015.

[36] D. Shasha, F. Llirbat, E. Simon, and P. Valduriez. Transaction Chopping: Algorithms and Performance Studies. *TODS*, 20(3), 1995.

[37] B. Steensgaard. Points-To Analysis in Almost Linear Time. In *POPL*, 1996.

[38] M. Stonebraker, S. Madden, D. J. Abadi, S. Harizopoulos, N. Hachem, and P. Helland. The End of an Architectural Era: (It's Time for a Complete Rewrite). In *VLDB*, 2007.

[39] A. Thomson, T. Diamond, S.-C. Weng, K. Ren, P. Shao, and D. J. Abadi. Calvin: Fast Distributed Transactions for Partitioned Database Systems. In *SIGMOD*, 2012.

[40] S. Tu, W. Zheng, E. Kohler, B. Liskov, and S. Madden. Speedy Transactions in Multicore In-Memory Databases. In *SOSP*, 2013.

[41] T. Wang and R. Johnson. Scalable Logging Through Emerging Non-Volatile Memory. In *VLDB*, 2014.

[42] Y. Wu, J. Arulraj, J. Lin, R. Xian, and A. Pavlo. An Empirical Evaluation of In-Memory Multi-Version Concurrency Control. In *VLDB*, 2017.

[43] Y. Wu, C.-Y. Chan, and K.-L. Tan. Transaction Healing: Scaling Optimistic Concurrency Control on Multicores. In *SIGMOD*, 2016.

[44] Y. Wu and K.-L. Tan. Scalable In-Memory Transaction Processing with HTM. In *USENIX ATC*, 2016.

[45] C. Yan and A. Cheung. Leveraging lock contention to improve oltp application performance. In *VLDB*, 2016.

[46] C. Yao, D. Agrawal, G. Chen, B. C. Ooi, and S. Wu. Adaptive Logging: Optimizing Logging and Recovery Costs in Distributed In-Memory Databases. In *SIGMOD*, 2016.

[47] Y. Zhang, R. Power, S. Zhou, Y. Sovran, M. K. Aguilera, and J. Li. Transaction Chains: Achieving Serializability With Low Latency in Geo-Distributed Storage Systems. In *SOSP*, 2013.

[48] W. Zheng, S. Tu, E. Kohler, and B. Liskov. Fast Databases With Fast Durability and Recovery Through Multicore Parallelism. In *OSDI*, 2014.

APPENDIX

A. IMPLEMENTATION

In this section, we describe the implementation details of the logging-and-recovery framework adopted in Peloton. Our implementation faithfully follows that of SiloR [48], a main-memory DBMS that is optimized for fast durability. We discuss some possible optimization techniques at the end of this section.

A.1 Logging

The DBMS spawns a collection of worker threads for processing transactions and a collection of logger threads for persisting logs. Worker threads are divided into multiple sub-groups, each of which is mapped to a single logger thread.

To minimize the logging overhead brought by frequent disk accesses, the DBMS adopts group commit scheme and persists logs in units of epochs. This requires each logger thread to pack together all its transaction logs generated in a certain epoch before flushing them into the secondary storage. To limit the file size and facilitate log recovery, a logger thread truncates its corresponding log sequence into a series of finite-size log batches, and each batch contains log entries generated in multiple epochs. The DBMS stores different log batches in different log files, and this mechanism simplifies the process of locating log entries during log recovery.

Each logger thread in the DBMS works independently, and this requires us to create a new thread, called *pepoch* thread, to continuously detect the slowest progress of these logger threads. If all the loggers have finished persisting epoch i, then the pepoch thread writes the number i into a file named `pepoch.log` and notifies all the workers that query results generated for any transaction before epoch $i + 1$ can be returned to the clients.

and the batch size to 100 epochs.

A.2 Recovery

The DBMS starts log recovery by first reading the latest persisted epoch ID maintained in the file `pepoch.log`. After obtaining the epoch ID, the DBMS reloads the corresponding log files and replays the persisted log entries. For tuple-level logging mechanisms, including physical logging and logical logging, the DBMS replays the log files in the reverse order than they were written. This mechanism minimizes the overhead brought by data copy. However, for transaction-level logging mechanism, or command logging, the DBMS has to replay transaction logs following the transaction commitment order, as described in this paper.

A.3 Possible Optimizations

Existing works have proposed several mechanisms for optimizing the performance of logging-and-recovery mechanism in DBMSs. However, these optimizations may not be suitable for main-memory DBMSs.

A widely used optimization mechanism in disk-based DBMSs is log compression [9, 21], which aims at minimizing the log size that is dumped to the disk. We did not adopt this mechanism, as SiloR's experiments have shown that compression can degrade the logging performance in main-memory DBMSs [48]. Some DBMSs adopt delta logging [35] or differential logging [20] to persist only the updated columns of the tuples for a transaction. While reducing the log size, these mechanisms are specifically designed for multi-version DBMSs. We did not adopt these optimization schemes, as our goal is to provide a generalized logging mechanism for both single-version and multi-version main-memory DBMSs. Kim et al. [19] implemented a latch-free scheme to achieve scalable centralized logging in a main-memory DBMS called Ermia. Their mechanism is designed for DBMSs that execute transactions at snapshot isolation level. We keep using SiloR's design as Peloton provides full serializability for transaction processing. Hekaton [10]'s logging implementation is very similar to ours, and it also avoids write-ahead logging and adopts group commit to minimize overhead from disk accesses. We have already included its optimization schemes in our implementation.

Algorithm 1: Build local dependency graph.

Input : a sequence of operations $O = \{o_1, o_2, \ldots, o_n\}$ in a stored procedure p
Output: a local dependency graph g containing a set of slices $S = \{s_1, s_2, \ldots, s_m\}$

Initialization:
$S = \{\{o_i\} \mid o_i$ is an operation in $O\}$;

Merge slices:
while *exists* o_p *and* o_q *respectively from* s_i *and* s_j *that are data-dependent* **do**
  merge s_i and s_j into a new slice s_k;

Build graph:
foreach *slice pair* $\langle s_i, s_j \rangle$ *in* S **do**
  if *exists* o_p *and* o_q *respectively from* s_i *and* s_j *where* o_q *is flow-dependent on* o_p **then**
    add a dependency edge from s_i to s_j;

Break cycles:
foreach *slice pair* $\langle s_i, s_j \rangle$ *in* S **do**
  if s_i *and* s_j *are mutually (indirectly) dependent* **then**
    merge s_i and s_j into a new slice s_k;

Algorithm 2: Build global dependency graph.

Input : local dependency graphs $G = \{g_1, g_2, \ldots, g_n\}$ from each stored procedure
Output: a global dependency graph $\mathcal{G}$ containing a set of blocks $B = \{b_1, b_2, \ldots, b_m\}$

Initialization:
$B = \{\{s_i\} \mid s_i$ is a slice of a graph g_i in $G\}$;

Merge blocks:
while *exists* s_p *and* s_q *respectively from* b_i *and* b_j *that are data-dependent* **do**
  merge b_i and b_j into a new block b_k;

Build graph:
foreach *block pair* $\langle b_i, b_j \rangle$ *in* B **do**
  if *exists* s_p *and* s_q *respectively from* b_i *and* b_j *where* s_q *is dependent on* s_p **then**
    add a dependency edge from b_i to b_j;

Break cycles:
foreach *block pair* $\langle b_i, b_j \rangle$ *in* B **do**
  if b_i *and* b_j *are mutually (indirectly) dependent* **then**
    merge b_i and b_j into a new block b_k;

Merge slices:
foreach *block* b *in* B **do**
  merge slices originated from the same stored procedure;

B. ALGORITHMS

This section presents the algorithms for constructing two statically extracted graphs: local dependency graph (shown in Algorithm 1) and global dependency graph (shown in Algorithm 2).

C. TPC-C

Figure 21 shows a simplified global dependency graph of the TPC-C benchmark generated by PACMAN's static analysis. Stored procedures in this benchmark provide a warehouse ID as an input parameter for each instantiated transaction. Note that read-only transactions are ignored as these transactions do not generate any logs during execution.

D. LOGGING PERFORMANCE

In this section, we measure how SSD bandwidth and latency

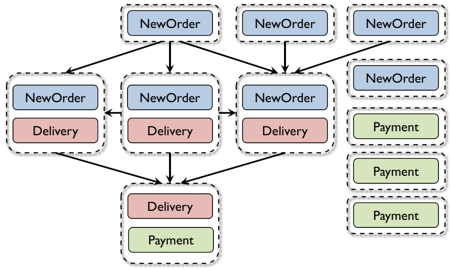

Figure 21: Global dependency graph for TPC-C. Each solid rectangle represents a slice. Slices within the same dashed rectangle belong to the same block.

	w/ checkpoint			w/o checkpoint		
	PL	LL	CL	PL	LL	CL
1 SSD (MB/s)	352	347	250	274	252	34
2 SSDs (MB/s)	468	460	246	280	252	34

Table 2: Overall SSD bandwidth.

	w/ `fsync`			w/o `fsync`		
	PL	LL	CL	PL	LL	CL
1 SSD (ms)	38	33	14	10	10	7
2 SSDs (ms)	25	24	11	10	10	7

Table 3: Average transaction latency.

can affect the performance of different logging schemes reported in Figure 11.

Table 2 shows that, using one SSD, tuple-level logging (including PL and LL) generates approximately 350 MB/s and 260 MB/s log data with and without checkpointing threads, respectively. The throughput is increased to 460 MB/s when persisting data to two SSDs with checkpointing enabled. Correspondingly, we observed in Figure 11 that adding one more SSDs can greatly improve the performance of tuple-level logging in terms of both throughput and latency. These results altogether indicate that the throughput drops and latency spikes observed in the experiments were due to the limitation of SSD bandwidth. Transaction-level logging's performance is not influenced by the SSD bandwidth, because it only generates small amounts of data. This is essentially a major benefit of transaction-level logging.

To analyze the effect of SSD latency, we compare the average transaction latencies for two settings: (1) when `fsync` is used to flush the log buffers (which corresponds to the latencies shown in Figure 11 in the revised version of our paper), and (2) when `fsync` is not used at all. Table 3 shows this comparison with checkpointing disabled. The experiment results show that invoking `fsync` operation can result in much higher latency for tuple-level logging (i.e., PL and LL) compared to transaction-level logging (i.e., CL), and the latencies achieved by tuple-level logging can be drastically reduced when committing transactions without invoking `fsync` operation. Considering that the log size generated by tuple-level logging is $\sim$10X larger than that of transaction-level logging, these results altogether indicate that `fsync` is a real bottleneck for DBMS logging, and its overhead is exacerbated when persisting larger amounts of data.