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MEI, Xiupei; ASHRAF, Imran; MA, Xiaoxue; ZHANG, Hao; WEI, Zhengyuan; WANG, Haipeng; CHAN, W. K.

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Execution Repair for Spark Programs by Active Maintenance of Partition Dependency

XIUPEI MEI, IMRAN ASHRAF, XIAOXUE MA, HAO ZHANG, ZHENGYUAN WEI, HAIPEG WANG, (Graduate Student Member, IEEE), AND W. K. CHAN, (Member, IEEE)
Department of Computer Science, City University of Hong Kong, Hong Kong
Corresponding author: W. K. Chan (wkchan@cityu.edu.hk)

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ABSTRACT  Spark programs typically codify to reuse some of their generated datasets, called partition instances, to make their subsequent computations complete in a reasonable time. At runtime, however, the underlying Spark platform may independently delete such instances or accidentally cause these instances inaccessible to the program executions. Those instances will invalidate the computation assumption made in writing these programs that such depending instances are present, which leads performance bloat and even breaks the executions. In this paper, we present FAR, a novel and effective framework to handle such performance bloat and actively repair the executions by maintaining the instance dependencies in Spark program executions. FAR monitors the partition instance lifecycle activities at all levels, and determines from the execution plan of the current Spark action in the current program execution on whether a partition instance will have a dependency relation with a later one underlying the computation of that action. The experimental results showed that with the active execution repair mechanism of FAR, when some dependency partition instances were inaccessible, programs can achieve 7.3x to 67.0x speedup in re-generating them. The results also interestingly revealed that the program executions actively repaired by FAR can run to successful completion in environments with 1.7x-2.0x fewer available memory.

INDEX TERMS  Debugging, execution repair, dataset dependency, big data.

I. INTRODUCTION
Programs running on a cluster of Spark nodes [2] are widely used in practice [36]. They accept inputs containing an arbitrary number of records to compute results. These programs, such as page rank [28] or hot topics [29], generate many sets of intermediate datasets. Each of such sets is called a data partition[2], where the partition instance contains the actual data records for processing. Each data partition is bound to an RDD (Resilient Distributed Dataset) [2], which is the most important data structure used in program code. Such a program manipulates RDD instances, thereby using the corresponding data partitions to systematically compute the results from its input through a sequence of Application Programming Interface (API) calls. Nonetheless, keeping all these intermediate partition instances is impractical.

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be significantly compromised by excessive partition creation and deletion of the same partition instances.

At the program level, with respect to $D^1$ and its belonging RDD instance $R$, application developers may add persistence instructions (e.g., $R$.persist() and $R$.unpersist()) in their program code $C$ to retain or delete the corresponding partition instances of $R$ in an all-or-nothing manner. Program-level strategies are unaware of operations done at the platform level. Thus, the internal operations of Spark$_\text{base}$ may invalidate any heuristics written in $C$ that rests on the assumption that $D^1$ is always persistent for subsequent uses.

In this paper, we present FAR, a novel and effective framework to handle a class of performance bloat that equivalent partition instances of RDDs are excessively generated and deleted. To the best of our knowledge, FAR is the first systematic approach to address this problem.

FAR is built atop two insights on programs for Big Data processing. First, in a program execution $\sigma$, for each operation to produce a result (rather than an intermediate RDD), each partition $D$ can precisely pair up with a set of outstanding uses (called budget) that must appear in current round of execution by $\sigma$. Second, if the current instance for $D$ is deleted before fulfilling all such uses, Spark$_\text{base}$ will generate a new instance of $D$.

The basic idea of FAR is to compute the budget of each partition for each such operation in the evaluation phase of $\sigma$ to extract the dependency relation between partitions relevant to the current operation. Moreover, during the concrete execution phase corresponding to the above evaluation phase, FAR does the following: On handling the request of an instance $D^1$ of partition $D$, FAR adjusts the budget of each partition that $D$ depends on. When the budget of a partition is exhausted, FAR instructs Spark$_\text{base}$ to delete the instance of that partition. On contrary, if the budget of a partition $D$ has not been exhausted but no instance of it is found, FAR increases the budget of each partition that $D$ depends on. FAR also instructs Spark$_\text{base}$ to annotate $D$ as reserve so that if a new instance of $D$ is generated, that instance will be kept rather than deleted right after the current use.

FAR is designed with ease of use, high efficiency, and versatility in mind. We have implemented FAR as a Spark component. Application developers can simply insert pairs of FAR’s API calls into each code region that leads to a performance bloat in their program code (as illustrated in Section IV.E) or enable it in the configuration file to make Spark$_\text{base}$ use FAR as the default.

We evaluate FAR on six representative applications taken from GraphX [6] and GitHub repositories [7] with real-world datasets as the evaluation benchmarks. We have compared FAR to the state-of-the-practice Spark platform (i.e., referred to as Spark$_\text{base}$ in this paper). The main results show that (1) in the scenarios of inaccessible dependency partition instances, FAR can achieve 7.3x to 67.0x speedup in re-generating them compared to Spark$_\text{base}$, and (2) in memory stringent scenarios, FAR can enable program executions to complete successfully in environments with 1.7x to 2.0x fewer available memory than Spark$_\text{base}$. The result also shows that for program executions that can run normally on Spark$_\text{base}$, FAR only incurred no more than 1.39% additional runtime slowdown overhead over Spark$_\text{base}$.

The main contribution of this work is threefold.
- This paper presents the first work, called FAR, to address a class of performance bloat that the equivalent partition instances are excessively produced.
- We show the feasibility of FAR by implementing it as a Spark component and demonstrate its ease of use.
- This paper presents an evaluation of FAR and shows that FAR is effective and efficient. The result also shows that FAR can enable programs to run to completion in situations unable to be handled by Spark$_\text{base}$.

The rest of this paper is organized as follows. We firstly revisit the preliminaries in Section II. Through a motivating example in Section III, we introduce the problem to be solved by FAR, which is presented in Section IV, followed by its evaluation and further discussion in Sections V and VI. We review the related work in Section VII and conclude this work in Section VIII.

II. PRELIMINARIES

A. THE SPARK FRAMEWORK

Spark [2] provides a runtime denoted as Spark$_\text{base}$. It provides dataset operations for applications to compute data records modeled as Resilient Distributed Dataset (RDD) [2], where each RDD instance represents a partitioned collection of data records. Each data partition is an array for keeping data records kept in the primary storage and second storage, which we generally refer to as the memory in Spark.

Transformation (e.g., map, filter, join, and groupByKey) and action (e.g., reduce, collect, count, first, and foreach) are two kinds of dataset operations for Spark programs. When a transformation $T$ is applied on an RDD instance $R_X$, a new RDD instance $R_Y$ is created. Each partition in $R_Y$ depends on one or multiple partitions of $R_X$, which is determined by the function type of $T$. During a program execution $\sigma$, all the created RDD instances and the transformation relations between them construct a lineage graph $G$ [2].

Moreover, for each partition $P_Y$ in $R_Y$, we model its dependency as a 3-tuple $(P_Y, < P_X >, F_T)$, where the second element is a set of partitions in $R_X$ that $P_Y$ depends on and the third element is a transformation function of $T$. All the partitions and the dependency relations between them construct a partition dependency graph $G_P$.

Note that during the program execution, a partition $P$ may be materialized (i.e., populated with data records) zero or multiple time(s) and each such operation produces a partition instance. For ease of reference, we refer to the partition instance of $P$ with occurrence id $i$ as $P_i$. Note that, for partition $P$, all its partition instances are equivalent.

A typical program execution consists of two alternating phases, the lineage graph construction phase and the concrete execution phase.
During the lineage graph construction phase, by executing transformation operations, \( \sigma \) creates a set of RDD instances and appends them to the lineage graph \( G_\sigma \). This process continues until an action \( \Lambda \) on some RDD instance \( R \) is invoked, which starts a concrete execution phase to compute all the partitions of \( R \). The completion of \( \Lambda \) starts the next round of lineage graph construction phase.

The dataflow between partitions is modeled as a dependency. For example, to generate \( P^1_X \) of \( P_Y \), whose dependency is \( (P_Y, < P_X >, F_Y) \), Spark\_base will ensure all the partition instances of its depending partitions in \( < P_X > \) are accessible followed by applying the function \( F_Y \) on them to produce \( P^1_Y \). If a partition, say \( P_X \), in \( < P_X > \) is persistent (where the possible states of a partition are defined in the next subsection), Spark\_base creates a dependency from the current instance, say \( P^1_X \), of \( P_X \) to \( P^1_Y \). On the other hand, if no partition instance of \( P_X \) is found, Spark\_base creates a dependency to \( P_X \) to indicate that it should generate an instance of \( P_X \). Therefore, to ensure a partition to have a partition instance, there is a dependency graph to end at either a partition instance or a partition. In the latter case, a partition instance, say \( P^2_X \), is required to be generated so that the dependency now ends at \( P^2_X \). We refer to the above dependency generation as the establishment procedure of dependency.

**B. STATE TRANSITIONS OF RDD AND PARTITION**

Fig. 1 depicts a state-transition diagram modeling the lifecycle of an RDD instance in Spark\_base. Spark\_base provides two RDD operations, **persist** and **unpersist** to handle the reuse of generated datasets. These operations, although happen during the lineage graph construction phase and transit the states of RDD instances in \( G_\sigma \), are not recorded in the lineage graph being constructed by Spark\_base.

When an RDD instance \( R \) is declared, \( R \) is created with the **ephemera** state. When \( \sigma \) executes \( R.unpersist() \), \( R \)'s state transits to **reserved**. A partition \( P \) of \( R \) is **ephemera** or **reserved** (depicted as square rectangles with dashed or solid border) if \( R \) is in **ephemera** or **reserved** state, respectively.

Consider the establishment procedure of dependency (\( P^1_Y, < P_X >, F_Y \)). When a partition instance \( P^1_X \) is generated, suppose that \( P_X \) is **ephemera**, \( P^1_X \) will be only available within such procedure and is discarded after \( F_Y \) is completed. Alternatively, suppose that \( P_X \) is **reserved**, \( P^1_X \) will be kept in the memory. We refer to the partition as **persistent** (depicted as shaded rectangles) if its instance is already kept in memory. As long as \( P_X \) is **persisted**, the subsequent creation of other dependency will reuse \( P^1_X \) instead of generating new instances of \( P_X \).

When \( R \)'s state is **reserved** and \( \sigma \) executes \( R.unpersist() \), \( R \)'s state transits to **ephemera**, and all its **persisted** partition instances are deleted from the memory.

The operation \( sys.evict(P) \) models Spark\_base to select a **persisted** partition \( P \) for reclaiming the memory space from \( P \)'s occupation. When Spark\_base invokes \( sys.evict(P) \), its instance \( P^1 \) is deleted from the memory (and its memory occupation is de-allocated), and \( P \) is changed to a **reserved** partition. An intention behind the above design is to hide the deletion’s impact on partition instance reuse in \( \sigma \), which simplifies the handling of such **missing partition instances** at the program level. For instance, suppose that there is a persisted partition \( P \) and \( P^1 \) is kept for multiple uses in \( \sigma \). After \( sys.evict(P) \) is invoked, \( P^1 \) is removed, and \( P \) transits to **reserved**. Upon the next creation of some dependency instance that uses \( P \), \( P^{k+1} \) is populated with new data records, and \( P \) transits to **persistent** again. The newly generated \( P^{k+1} \) is kept for possible use in the subsequent part of \( \sigma \).

**III. MOTIVATING EXAMPLE**

In this section, we present a motivating example.

The exemplified program implements the Floyd-Warshall algorithm to find the shortest paths in a weighted graph [9]. Let function \( f_{SP}(i, j, k) \) returns the shortest paths from vertex \( i \) to vertex \( j \) using the vertices from the set \( \{1, 2, \ldots, k\} \). Thus, \( f_{SP}(i, j, 0) \) returns the weight of edge \((i, j)\). For \( k = 1, 2, \ldots, N \), \( f_{SP}(i, j, k) \) can be computed as follows:

\[
 f_{SP}(i, j, k) = \min(f_{SP}(i, j, k-1), f_{SP}(i, k, k-1) + f_{SP}(k, j, k-1))
\]

Hence, the shortest paths between all vertices can be obtained by iteratively invoking \( f_{SP}(i, j, k) \) of every vertex pair \((i, j)\) for \( k = 1, 2, \ldots, N \).

Fig. 2 and Fig. 3 show the implementation of the Shortest Paths Program in Spark. In Fig. 2(a), \( updatePaths() \) is a helper function. It accepts an RDD instance \( D \) which models distances of all the paths, and returns a new RDD instance \( D' \) which contains the distances that some of which are reduced by passing through vertex \( k \).

The \( k \)-th invocation of \( updatePaths() \) constructs a lineage graph \( updatePaths_k \). Fig. 2(b) shows a simplified version of it. The variable \( D \) represents a source RDD instance (denoted as \( D_{k-1} \)) in \( updatePaths_k \). At line 8, \( \sigma \) uses \( D_{k-1} \) to create another RDD instance \( pathsToK \) (denoted as \( pathsToK_k \)). The graph \( updatePaths_k \) contains an edge from \( D_{k-1} \) to \( pathsToK_k \). This edge is labeled with \( filter() \), which indicates how each partition instance of \( pathsToK_k \) can be computed based on its dependency partitions in \( D_{k-1} \). For brevity, we do not show the label. Other nodes and edges are similarly created.
Fig. 3 shows four program versions of the Floyd-Warshall algorithm. Each version uses the graph edges as the initial paths, which is assigned to the variable $\mathcal{D}$ (at line 16, 23, 31, or 42). We refer such variable $\mathcal{D}$ as $\mathcal{D}_0$ and assume each partition of $\mathcal{D}_0$ is persistent. We also denote the RDD instance associating with variable $\mathcal{D}$ by $\mathcal{D}_k$ after the $k$-th invocation of $\text{updatePaths}$. These four versions iteratively invoke $\text{updatePaths}()$ $N$ times. They are different only on when and which RDD instances to be set into which particular RDD states.

In this example, each partition instance is assumed to take $O(1)$ space and each transformation function is assumed to take $O(1)$ time. In this way, we can focus our discussion on the number of dependency instances established when comparing the effects of RDD state operations codified in these versions.

Since the actual calculation is at the data partition level, in the sequel, again for simplicity, we suppose that each RDD instance contains one partition. We describe the example at the data partition level and use $\mathcal{D}_k$ for $k=0$ to $N$ to indicate the RDD instance or partition interchangeably.

**Version 1** is a straightforward implementation. A high-level lineage graph created at line 18 through the loop at lines 17–19 is depicted under the code in Fig. 3, where all the nodes and edges produced in $\text{updatePaths}()$ are hidden. In the first iteration, at line 18, $\text{updatePaths}()$ uses $\mathcal{D}_0$ to compute $\mathcal{D}_1$. Since version 1 has no RDD state operations, the state of $\mathcal{D}_1$ remains as ephemera. The lineage graph for the program execution is extended with the graph $\text{UpdatePaths}_1$ (see Fig. 2), which is depicted as a blue dashed arrow from $\mathcal{D}_0$ to $\mathcal{D}_1$ in Fig. 3. Similarly, $\mathcal{D}_2$ to $\mathcal{D}_N$ are returned by $\text{updatePaths}()$ from the remaining iterations (up to the third iteration).

Since $\mathcal{D}_1$ to $\mathcal{D}_N$ are ephemera, their instances will not be shared among the creations of dependency instances. As such, version 1 presents a typical problem that suffers from a severe performance bloat problem. For instance, when the collect action is performed (line 20) on $\mathcal{D}_3$, version 1 starts to establish the dependency of $\mathcal{D}_3$, which generated three instances of $\mathcal{D}_2$: $\mathcal{D}_1^1$ to compute $\text{pathsToK}_3$ at line 8, $\mathcal{D}_2^2$ to compute $\mathcal{D}_3^2$ at line 9, and $\mathcal{D}_3^3$ to compute $\mathcal{D}_3$ at line 11. Similarly, each instance of $\mathcal{D}_2$ also triggers three instances of $\mathcal{D}_1$. Hence, the time complexity of version 1 is $O(3^N)$. Since...
none of these instances is persisted, the space complexity of persist partitions in version1 is $O(1)$.

**Version 2** marks each $D_k$ for $k = 1$ to $N$ to be reserved (line 26). Therefore, after $D_{k-1}^1$ has been generated, it can be shared among the generations of $D_k^1$ and the nodes in UpdatePaths, Hence, the time complexity of version2 is $O(N)$. As $D_{k}^1$ to $D_{N-1}^1$ are not deleted by version2 after their uses, the space complexity of version2 is $O(N)$. In general, this is an impractical solution due to limited memory capacity in a cluster node. Thus, through the platform-level strategy, Spark$_{base}$ will sooner or later delete some partition instances, irrespective to whether they will later be used in generating $D_N^1$. version2 thus suffers from another instance of the performance bloat problem in program executions.

**Version 3** iteratively deletes $D_{k-1}^1$ from the immediate past iteration after $D_k^1$ has been generated (lines 36–37). We note that this coding style is advocated as a best practice to alleviate performance issues [6]. Consider the loop at lines 32–38. In the $k$-th iteration, at line 33, $D_{k−1}$ from the previous loop is in the persistent state and assigned to variable prev$D_k$; at line 34 and 35, $D_k$ is returned by updatePaths() and is set to reserved; at line 36, the collect() action generates $D_k^1$; and at line 37, version3 deletes $D_{k−1}^1$ and changes $D_{k−1}$ to ephemera. The time and space complexities for version3 are $O(N)$ and $O(1)$, respectively. The corresponding high-level lineage graph for the execution point at the end of the third iteration is depicted under the title of “No instance re-generation”.

Nonetheless, the above coding style becomes ineffective when partitions are no longer persistent according to the plan of version3. Consider the N-th iteration of loop 32–38 to generate $D_N^1$ where $D_{N−1}^1$ has been generated in the (N-1)-th iteration. Suppose that $D_{N−1}^1$ is deleted by Spark$_{base}$ to fulfill the data population requests from the current task or other tasks concurrently running on the same cluster node before generating $D_N^1$. The state of $D_{N−1}$ will be changed from persistent to reserved. In this case, when $D_{N−1}^1$ is about to generate, a new partition instance $D_{N−1}$ has to be re-generated first. Nonetheless, in the (N-1)-th iteration, after $D_{N−1}^1$ has been populated, $D_{N−2}^1$ as well as all previous instances have been deleted by version3. Thus, to re-generate $D_{N−1}^2$. Spark$_{base}$ recomputes every such depending partition based on the current partition dependency graph (start from reloading the input file to generate $D_{N−1}^2$) in an ad hoc manner. Since each such partition has been explicitly deleted by version3 via the use of unpersist() operations and their states are thus ephemera (see Fig. 1). Similar to version1, the time complexity of version3 in this scenario becomes $O(N^3)$. The corresponding high-level lineage graph is depicted under the title of “Needling instance re-generation”.

**Version 4** is revised from version3 by adding a persist() call at line 49 right after the unpersist() call at line 48. This can be viewed as a possible patch added by a developer to fix version3 after realizing the instance re-generation problem illustrated by version3. In this case, the persist() and unpersist() calls issued in the iterations for $k = 1$ to $N$ delete the partition instances of $D_0$ to $D_{N−1}$ but transit their states into reserved.

When there is no missing partition instance, version4 creates the same amount of dependency instances as version3. The time and space complexities in this scenario are $O(N)$ and $O(1)$, respectively. Consider the scenario of missing partition instances encountered by version3. The re-generated instances of $D_{N−1}^2$ to $D_N^2$ are shared among the dependency establishments as $D_0$ to $D_{N−1}$ are marked as reserved at line 49. However, although multiple instance re-generations for the same partition can be avoided, each such instance is kept persistently once generated. The space complexity becomes $O(N)$. Similar to version2, this is an impractical solution. Spark$_{base}$ will eventually delete some partition instances, irrespective to the remaining needs and logics of version4. It suffers from the performance bloat problem as well.

**IV. OUR PROPOSAL: FAR**

In this section, we present FAR. FAR is built on top of Spark$_{base}$ and realized as a Spark$_{base}$ component.

**A. OVERVIEW**

During the program execution, the partition states are dynamically changed by the program, Spark$_{base}$, and the system environment. Program executes the coded management instructions on RDD instances. When the system is going to be out of memory, Spark$_{base}$ selects and deletes some partition instances from the memory to reallocate the memory space [8]. This technique is particularly appealing to enable program executions to run to completion when the memory is stringent. Nonetheless, it is inadequate. As we have presented via a series of programs in the motivating example (Section III), the partition states will directly affect the creation of dependencies. During the creation procedure, failure to establish the dependency relations with other partition instances lead to severe performance bloat problem. A large amount of time and space resources are wasted during such procedure.

FAR is proposed to guard the creation of dependency instances during the execution by creating a period for them to share the equivalent partition instance. Among all possible execution points in $\sigma$, FAR strategically chooses the execution point of each action invocation to identify partitions with outstanding uses in each concrete execution phase with respect to all the partitions belonging to the target RDD instance of the dataset action (e.g., the RDD instance $R$ in $R.collect())$. It automatically tracks (i.e., reserves and deletes) these identified partitions not only during the concrete execution phase but also whenever there is any ad hoc platform deletion of any partition, which the latter further identifies partitions for additional outstanding uses with respect to the partition needed to be deleted. A new round of partition generation may trigger a further round of partition deletion,
and vice versa. FAR strives for a balance between (lazy) partition retention and (lazy) partition deletion to advance the state of the art to make Spark\textsubscript{base} able to serve a wider spectrum of scenarios.

FAR provides two API functions, enableFAR() and disableFAR(), for application developers to enable and disable FAR in their application code, respectively. It also provides a configuration option in Spark\textsubscript{base} so that application developers need not to add FAR API calls to their code.

FAR maintains an analysis state $\Sigma_\sigma$ for $\sigma$, where $\Sigma_\sigma$ is a triple $\langle$target, P, R$\rangle$, where target is the RDD instance associating with the invoked dataset action in the current concrete execution phase, P is the set of all persistent partitions kept in Spark\textsubscript{base}, and R is a map which stores the budget on the outstanding uses (or budget for short) of each partition involved directly or indirectly in computing target. FAR consists of two core algorithms, which will be presented in the next two subsections.

### B. ALGORITHM 1: PARTITION IDENTIFICATION

On invoking a dataset action $A$ (e.g., inst.collect()), ONACTIONINVOKED(inst) in Algorithm 1 is called, where inst is the RDD instance associating with $A$. For ease of reference, we denote the set of partitions of inst by inst partitions and the set of all the direct dependency partitions of a partition $p$ by p dependencies.

The procedure ONACTIONINVOKED() first keeps inst to target (line 3). It retrieves from Spark\textsubscript{base} the set of all persistent partition instances currently maintained by Spark\textsubscript{base} and keeps their references in set P via function getPersistentState() (line 4). It also recursively computes the number of outstanding uses on each dependency partition starting from inst partitions by calling GETOUTSTANDINGUSAGE() (line 5), which in essence traverses the partition dependency graph, and keeps them in map R. At line 6, it invokes CHECK(), which checks the budget of each such partition, and reserves the partition (line 29) if the partition is ephemera and its budget is larger than one (lines 6–7), where persistPartition(part) marks the part as reserved and sets the flag part.FAR to true.

The procedure GETOUTSTANDINGUSAGE() accepts a set of partitions that each needs to be generated and returns the additional budget of each dependent partition. It first creates a map C to store the number of times each partition visited and a queue Q to keep the partitions to be visited (lines 13–14). Q is initialized with the partitions in parts. Then, the procedure visits each partition $d$ in Q. In each iteration, it checks whether $d$ is currently persisted in Spark\textsubscript{base} and whether $d$ has been visited before. If neither is the case, this indicates that $d$ will be generated in the current concrete execution phase and its dependency partitions should be computed first. So, the procedure adds all the dependent partitions of $d$ to Q for traversal (lines 17–19). Then, the procedure updates the map C to keep a budget on $d$: If $d$ is currently in C, its budget (denoted as C[d]) is incremented by 1; otherwise, C[d] is set to 1 (line 20). As the partitions in parts are also budgeted during these node visiting rounds, these initial visits are deducted from C to avoid duplicated budgeting (line 22). The resultant C is returned.

### C. ALGORITHM 2: PARTITION TRACKING

FAR monitors the state changes of partitions not only in concrete execution phases but also whenever there is any need of ad hoc deletion of partition instances. More specifically, whenever an instance of a reserved partition has been generated, ONPARTITIONPERSISTED() is invoked (lines 1–12), and whenever a persistent partition instance is deleted, ONPARTITIONEVICTED() is invoked (lines 14–24).

ONPARTITIONPERSISTED: During the generation of part, when a reserved partition part has been populated with data by Spark\textsubscript{base}, FAR updates the budget on its persistent dependency partitions and deletes their instances if their...
budgets have been exhausted: FAR first gets the actual usage information by calling \texttt{TRVERSE\(\text{part}\)} (line 3), which conducts a reachability analysis starting from \textit{part} and returns the number of actual uses of each reachable \textit{persistent} partition instance in \textit{P}. More specifically, in the procedure \texttt{TRVERSE()}, a map \textit{U} and a queue \textit{Q} are created to store the visit counts of each visited partition and partitions pending to be visited (initialized with \textit{part}’s dependency partitions) (lines 35–36). Then, the procedure iteratively takes a partition from \textit{Q} to visit until \textit{Q} is empty (lines 37–43). During each visit on partition \textit{d}, it increases the actual use of \textit{d} in \textit{U} (denoted as \textit{U}[\textit{d}]) by 1 (line 39). Then, it checks whether \textit{d} has been persisted. If this is not the case, \textit{d}’s dependency partitions are appended to \textit{Q} for further visit (lines 40–42). Finally, \textit{U} is returned to the caller.

After the actual use count on each persistent partition is computed and kept in \textit{U}, FAR updates the budget on each partition in \textit{R} (lines 4–10). More specifically, for each partition \textit{d} in \textit{U}, the budget \textit{R}[\textit{d}] is deducted by the actual use count \textit{U}[\textit{d}] (line 5). If \textit{R}[\textit{d}] becomes 0, it indicates the budget on \textit{d} has been exhausted. If this is the case, the physical storage of \textit{d} is removed from memory via \texttt{removePartition\(\text{d}\)}\footnote{Please refer to Section V.A for the details of \texttt{removePartition}} (line 7), where the actual deletion is left by \texttt{Spark\_base}, and \textit{d} is also removed from \textit{P} (line 8). A special consideration is that to avoid interference with the application logic, before the marking for deletion on \textit{d}, FAR also checks whether \textit{d} is reserved by itself beforehand. Otherwise, FAR will not mark it for partition deletion. Finally, \textit{part} is included in \textit{P} (line 11).

\texttt{ONPARTITION\_EVICTED}: The procedure firstly removes \textit{part} from \textit{P} (line 16), and updates the budgets on the outstanding uses of all other partitions if these partitions are directly or indirectly dependency partitions of \textit{part} (lines 17–24). More specifically, FAR checks whether \textit{part}’s budget (denoted as \textit{R}[\textit{part}]) is positive, which indicates whether \textit{part} is referenced in the later part of the concrete execution phase. If this is the case, FAR computes the budgets of the outstanding uses on other partitions that \textit{part} depends on by calling the procedure \texttt{GETOUTSTANDING\_USAGE} (We note that at line 18, \texttt{GETOUTSTANDING\_USAGE()} accepts a list of partitions as its input, \textit{part} is packed into a list). After the latest budget on each such partition, say \textit{d}, is computed and kept in \textit{C}, FAR increases the budget on \textit{d} at line 20, and reserves \textit{d} if \textit{d} is currently ephemera and will be used later via \texttt{CHECK()} (line 21).

FAR also monitors failure exceptions during each concrete execution phase. Once a data loss event is triggered by \texttt{Spark\_base}, FAR conducts a state refresh by calling the \texttt{ON\_FAILURE\_OCCURS()} procedure before the default recovery mechanism of \texttt{Spark\_base} is triggered. The purpose is that the data loss invalidates FAR’s internal state for further analysis. Hence, in \texttt{ON\_FAILURE\_OCCURS()}, \textit{P} is firstly re-computed (line 27), and \textit{R} is re-calculated by calling \texttt{GETOUTSTANDING\_USAGE()} with all partitions of the \textit{target} instance as input (line 28). Note that although all the partitions are passed for analysis, the procedure only returns the analysis results on those partitions that have not yet been evaluated, as the partitions evaluated prior to the failure point are skipped. Finally, each ephemera partition in \textit{R} is marked as reserved if its budget is still greater than one.

D. DISCUSSION ON DESIGN AND NOVELTY OF FAR
FAR has three aspects of novelty in its design.

First, FAR identifies and adjusts the budgets of relevant partitions at hybrid levels: collectively at the lineage graph level when each concrete execution phase starts and individually at the partition level when a persistent partition instance is deleted by \texttt{Spark\_base}.

Consider a pure partition level strategy, which identifies such a partition when the partition is persistent in memory or marked as reserved. As illustrated in the motivating example, a partition not marked as reserved in the application will not be set into the reserved or persistent state. So, this strategy could not meaningfully start the tracking process at all. Consider another pure partition level strategy, which identifies a partition to be persistent when the partition is ephemera. Since most partitions in a typical program execution should be ephemera (for instance, see version3 in the motivating example, which reduces the space complexity from \textit{O}(N) to \textit{O}(1)), this alternative strategy will invoke numerous rounds of traversal on almost every partition instance. Moreover, if a persistent partition has been deleted by \texttt{Spark\_base}, the state of that partition will not be ephemera (see Fig. 1). Thus, this alternative strategy cannot correctly handle system deletion scenarios. It should also be noted that \texttt{Spark\_base} uses a strategy at the pure partition level, which is shown to be inadequate in Section V.

Consider a pure collective level strategy. A system deletion on a partition of an RDD instance will lead each partition of the RDD instance to trigger a round of graph traversal, which produces redundant computation demands (note that \texttt{ONPARTITION\_EVICTED()} in Algorithm 2 uses a finer-granularity, which suffices to serve that purpose). Besides, to the best of our knowledge, FAR is the first technique to propose handling these partitions. Since this strategy is built on top of FAR, without FAR to lay down the groundwork, it would be more difficult to be discovered.

Second, FAR chooses to (i) keep more persistent partition instances (than \texttt{Spark\_base}) even when free memory locations are in shortage and (ii) applies a partition deletion strategy through \texttt{Spark\_base} (e.g., via \texttt{ONPARTITION\_EVICTED()} of Algorithm2). As a comparison, \texttt{Spark\_base} only chooses to delete partitions. We can view that our strategy forms a kind of two-player game (where FAR and its underlying \texttt{Spark\_base} to represent two competing players) to find an equilibrium feasible to both players (if possible), which is novel.

Last, but not the least, FAR simplifies the application code by raising the level of code abstraction on handling the persistence aspect of RDD instances from a procedural programming approach to an annotation approach (e.g., via \texttt{enableFAR()} and \texttt{disableFAR()} in the application code). It will
be exemplified in Section E and will be used in our evaluation on FAR in Section V. To the best of our knowledge, FAR is the first framework to provide such supports to application developers.
budget on $D_2$’s outstanding uses is 3, which indicates that $D_2$ will be re-generated. FAR computes the new budget on $D_2$ based on the current state kept in $P$ (line 18 in Algorithm 2), and the result is $C = \{D_0 = 3, D_1 = 3, pathToK_1 = 1, pathFromK_1 = 1, pathByK_1 = 1, pathToK_2 = 1, pathFromK_2 = 1, pathByK_2 = 1\}$. These budgets are added to $R$, and the state of $D_1$ is changed to reserved. In the rest of the execution, $D_1$ is persisted during $D_2$’s re-generation. ONPARTITIONPERSISTED() is invoked with $D_2$ when $D_2$ is generated. The outstanding uses of other partitions are computed and kept in $U$, where $U = \{D_1 = 3, pathToK_2 = 1, pathFromK_2 = 1, pathByK_2 = 1\}$. As all $D_1$’s budget has been exhausted, $D_1$ is deleted by FAR.

Therefore, by enabling FAR on top of version 1 (to become version 5), its time and space complexity are $O(N)$ and $O(1)$, respectively, regardless of whether or not partitions need to be re-populated, which cannot be achieved by Sparkbase alone in the four versions shown in Fig. 3, or any combination of them.

V. EVALUATION

In this section, we present the evaluation on FAR by comparing it to the original Spark platform with default configuration (denoted as Sparkbase) [8]. We aim to answer the following two key questions:

- **RQ1**: Can FAR effectively address the performance bloat problem faced by Spark applications in situations incurring the performance bloat problem?
- **RQ2**: Is FAR efficient compared to Sparkbase in the scenario of normal program executions?

For RQ1, we consider two sub-scenarios which to the best of our knowledge, are representative. Recall that a program execution will start its concrete execution phase at each encountered dataset action performed on an RDD instance. During the creation of the related dependency instances, there may be computation errors or system errors to prevent the concrete execution phase to run smoothly. We refer to it as the first sub-scenario (Scenario 1) by failing a program execution when the concrete execution phase is about to start as what Zaharia et al. did in their experiment [2].

Alternatively, the concrete execution phase can proceed, but the underlying cluster nodes may have insufficient free memory locations. In such cases, some partitions of a target program execution will change their states from persistent to reserved due to platform deletion of their instances. We refer to it as the second sub-scenario (Scenario 2) by systematically varying the amount of available memory of executor nodes.

We also note that during program development, a program version may contain functional bugs (e.g., unable to process a particular record with unexpected contents or in an unexpected format), resulting in program execution failure when processing a test dataset. In typical Spark configurations, when a failure occurs, the program version may intentionally re-run for a few times (e.g., 4 times) before execution abortion. When such a failure occurs in the course of establishing a dependency, Sparkbase re-generates that instance. Thus, the two sub-scenarios also help evaluate to what extent FAR can assist application developers in testing and debugging their programs incurring critical failures by reducing the runtime of their executions involved.

It is also quite common that a particular program execution may not encounter any performance bloat problem due to dependency establishment failure, hence not triggering the re-generation process of Sparkbase of corresponding partition instances. Intuitively, the memory consumption required by programs highly depend on the scale of the input that to be processed. Therefore, although the capacity of underlying infrastructure can be large, the overall resources and the costs could become major issues when computing over larger datasets and/or demanding more accurate results. For instance, when running on a cloud computing platform, multiple big data applications may be parallelly executed on the same cluster. The available resources become more elastic and the platforms perform more interventions than private clouds. Therefore, it is interesting to see how FAR performs under stringent memory resource scenarios.

For RQ2, we consider the normal situation (Scenario 3) that neither a system failure nor a memory resource shortage occurs. Intuitively, in such situations, FAR will incur an additional overhead in performing its state initialization and more overheads during concrete execution phases. In RQ2, we aim to evaluate whether FAR is efficient, i.e., whether the overhead introduced by FAR is acceptable. To assess the performance, we evaluate the runtime slowdown of FAR under this scenario and compare it with Sparkbase.

The whole evaluation procedure taken around 120 hours. All the evaluation results and the source code base of FAR are available at https://github.com/FAR-Data/.

A. IMPLEMENTATION

We have prototyped FAR as a module in Spark framework using the Scala language. When an execution started, the Spark driver was launched on the master node and a FARManager instance was created in it.

The manager got the schedule information (including jobs, stages and tasks) from Spark’s DAGScheduler instance and checked whether each partition was persistent by querying the BlockManagerMaster instance. To do that, we modified DAGScheduler and Block-ManagerMaster and so that FARManager was notified whenever any concrete execution phase was about to start, any partition was generated or removed. With such information, FARManager kept the outstanding uses of each partition and performed its algorithms accordingly.

Whenever FARManager needed to persist a partition, it updated the state of such partition on the driver and synchronized the changes to corresponding executors via DAGScheduler. When FARManager needed to delete a partition (removePartition() in Algorithm 2), it requested Block-ManagerMaster to send removeBlock messages to executors, which removed the corresponding dataset.
TABLE 1. Application benchmarks.

<table>
<thead>
<tr>
<th>Benchmarks (Abbr)</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ShortestPaths (SP)</td>
<td>Compute shortest paths to the given set of landmark vertices. [9]</td>
</tr>
<tr>
<td>WeaklyConnectedComponents (WCC)</td>
<td>Compute the connected component membership of each vertex and return a graph with the vertex value containing the lowest vertex id in the weakly connected component containing that vertex. [6]</td>
</tr>
<tr>
<td>PageRank (PR)</td>
<td>Run PageRank for a fixed number of iterations returning a graph with vertex attributes containing the PageRank and edge attributes the normalized edge weight. [6][28]</td>
</tr>
<tr>
<td>SVDPlusPlus (SVD++)</td>
<td>Implement SVD++ based on &quot;Factorization Meets the Neighborhood: a Multifaceted Collaborative Filtering Model&quot;. [41]</td>
</tr>
<tr>
<td>GreedyMaximalMatching (GMM)</td>
<td>An implementation of the greedy matching algorithm. [7]</td>
</tr>
<tr>
<td>Breadth-First-Search (BFS)</td>
<td>An implementation of the Breadth-First-Search algorithm. [7]</td>
</tr>
</tbody>
</table>

B. EXPERIMENTAL SETUP

1) ENVIRONMENT

The experiments were conducted on a server with 4 Intel Xeon E7-4850 v3 CPUs and 512GB memory, and with VMware ESXi [10], a bare-metal hypervisor running on it. To approach the real-world environment, we set up a cluster of 21 VM nodes on the server to run the experiments. Each node was a virtual machine instance configured with four vCPUs and 16GB memory, which is a commonly used configuration provided by cloud computing services (such as Amazon AWS\(^3\) and Microsoft Azure\(^4\)) for general purpose computing. This cluster configuration with 21 VM nodes was the maximum number of VMs that we can create in our server while keeping the server’s smooth running. Among these nodes, one served as the master node running the Spark driver process, and the other twenty nodes served as worker nodes of Spark executor. Each executor process was configured with 4 cores and 14GB memory.

The JVM version was 1.8.0_231-b11 and the Scala version was 2.11.8. HDFS shipped with Hadoop 2.7.3 was used to keep data. We compiled Spark source code with version 2.4.4 on the above setting as Spark base and compiling it as FAR in the evaluation.

2) BENCHMARKS

We used six benchmarks in the experiments. All these benchmarks are summarized in Table 1.

The Spark GraphX library is widely used in practice and many of its programs were used in various previous work [25], [26]. We used all the non-trivial benchmarks as our benchmarks: WeaklyConnectedComponents (WCC), PageRank (PR), SVDPPlusPlus (SVD++), and ShortestPath (SP). We also used implementations of two commonly used algorithms, GreedyMaximalMatching (GMM) and Breadth-FirstSearch (BFS) from GitHub [7].

The above six benchmarks have also been widely used in other works. In [6], the authors used PageRank and ConnectedComponents (an implementation to compute weakly connected components in a graph) to evaluate the performance of GraphX, Giraph and GraphLab [38], [39]. In [40], four widely used applications, including BreadthFirstSearch, PageRank, SingleSourceShortestPath (which is a special case of ShortestPaths in our motivating example) and WeaklyConnectedComponent are used to evaluate the efficiency of their work. We included all these benchmarks in our evaluation on FAR. Besides, we added two more benchmarks to seek for a wider generalization. All the benchmarks are using persist (or cache) and unpersist operations to keep and discard the intermediate datasets. In the experiment, we enabled FAR in configuration file so that all the concrete execution phases are protected to make fair comparisons.

3) DATASETS

We used two real-world datasets to evaluate the performance of FAR on these benchmarks. For SP, WCC, PR, GMM and BFS, we used the uk-2005-host graph dataset from WebGraph [11]. This dataset contained 39,459,925 nodes and 936,364,282 edges, and the graph was stored in a single file with a size of 15.32GB. For SVD++, as it is a widely used algorithm to build a recommendation system, we chose the Netflix Prize dataset [12] to evaluate its performance. The benchmark contained 100,480,507 ratings of 17,770 movies made by 480,189 users. The rating file size was 2.43GB. Both datasets were stored on HDFS and the data block size was set to the default value (i.e., 64MB). They have also been widely used in other works [13]–[15].

4) EXPERIMENTAL PROCEDURE

We set 3600 seconds as the timeout threshold for all the experiments, which was one order of magnitude higher than the time spent by these benchmarks to run to completion successfully. Setting a threshold one order of magnitude higher than the runtime needed to complete the baseline execution is a typical setting in software engineering experiments (e.g., [43]). We regarded a program execution as timeout if its total elapsed time of the execution larger than this threshold.

For answering RQ1 in Scenario 1, we applied the following procedure: We firstly ran each benchmark on Sparkbase because Sparkbase exhibited more constrained capacity in handling the benchmarks. More specifically, at the start of the concrete execution phase of the last dataset action (i.e., the last Spark job of each program execution), we failed one randomly chosen Spark executor, which caused the datasets in that executor inaccessible by other executors. This resulted in the following situation: all the partition instances
on the failed executor were cleaned up and Spark\textsubscript{base} arranged some other executors to re-generate the required missing partition instances and continued to complete the program execution. This strategy to fail a program execution was also used in [2] and [6].

For each program execution that we failed its executor, if the whole program execution did not finish before the timeout threshold, we terminated the program execution, and ended the experiments on this benchmark. Otherwise, we kept the execution logs, increased the number of iterations (starting from one) by one, and executed the benchmark. In short, we systematically increased the number of iterations until running a benchmark resulted in a timeout. As we are going to present in Section C, Spark\textsubscript{base} can handle 12 iterations on average on this set of benchmarks.

We then ran each benchmark on FAR using the same procedure. However, on each benchmark, FAR did not result in a timeout in each of the first 20 runs (i.e., program executions with one, two, . . . , 20 iterations). We also observed that the differences in various metrics between Spark\textsubscript{base} and FAR have become greater than an order of magnitude. We therefore ended the collection of statistics on FAR after the first 20 experiments on each benchmark. We note that using such a gap in duration to end an experiment is a typical setting in the experiments used in software engineering [44].

To answer RQ1 in Scenario 2, for each benchmark running on each of Spark\textsubscript{base} and FAR, we systematically varied the available memory that could be used by each executor. More specifically, for each benchmark, we configured it with 20 iterations and set the available memory for each executor to be 14GB, 13GB,..., 1GB to execute the benchmark. When each executor allocated with more than 8GB memory, the system did not remove any partition instance during the executions as there were sufficient memory locations for persisted partition instances, and when the memory allocation set to 1GB, the executions failed with the OutOfMemoryError exception due to insufficient heap memory space. Therefore, in this experiment, we only analyzed the data on these trials with 8GB, 7GB, . . . , 2GB as the memory size of each executor. To constrain the memory used by an executor, we configured the spark.executor.memory parameter, limiting executors to use no more than a certain amount of memory on the node, and thus the memory locations for persistent partition instances were also limited.

To answer RQ2, for each benchmark, we ran it for a fixed number of iterations. To make all the experiments consistent, we set the iteration number to 20, which was also the same with experiments in RQ1. We ran each benchmark with Spark\textsubscript{base} and FAR, respectively, for 20 times.

### C. ANSWERING RQ1 THROUGH SCENARIO 1

For each program execution, we measured the total elapsed time to complete the execution. Fig. 5 shows the results. The upper plot is for Spark\textsubscript{base} and the lower one is for FAR. In each plot, there are six lines, one line for each benchmark. Each point indicates a program execution where the x-value represents the number of iterations configured in the corresponding benchmark. The y-axis is the time spent for handling inaccessible partition instances. The time spent is calculated by \( t_x - t_x' \), where \( t_x \) and \( t_x' \) are the total elapsed time spent by the program execution with and without triggering re-generation of partition instances. Thus, the y-value of each point represents the overhead to handle re-generations of such inaccessible partition instances incurred by either Spark\textsubscript{base} or FAR for these program executions.

We observed that in both plots, the overall trend is that longer time is spent as \( x \) increases. However, after some point of \( x \)-value, the time spent for Spark\textsubscript{base} increases rapidly, and hits the timeout threshold (as indicated by the omissions of points). More specifically, Spark\textsubscript{base} hits the timeout limit after \( x = 5, 13, 14, 14, \) and 16 for benchmarks SVD++, PR, GMM, BFS, WCC, and SP, respectively. While for FAR, the spent time increases gently without omission in the plot. Also, on each benchmark, FAR takes either similar or much less time than Spark\textsubscript{base} for the same \( x \)-value.

We have also computed the speedup achieved by FAR over Spark\textsubscript{base}. Table 2 summarizes the results. The first column represents the benchmark. We collected the time.
spent incurred by both Spark\textsubscript{base} and FAR for these program executions without timeout. The 2\textsuperscript{nd} – 4\textsuperscript{th} (5\textsuperscript{th} – 6\textsuperscript{th}) columns show the mean (maximum) time spent by Spark\textsubscript{base}, FAR, and the ratio of them in these executions.

Table 2 shows that compared to Spark\textsubscript{base}, enabling FAR can achieve 3.7x to 13.2x mean speedup and 7.3x to 67.0x maximum speedup for the six benchmarks. The average of these mean and maximum speedups is 8.8x and 35.4x. The improvement of FAR over Spark\textsubscript{base} is large.

To analyze whether there is a significant difference between FAR and Spark\textsubscript{base} in reusing partition instances, we further analyzed individual program executions. We repeated the experiment, but at this time, we inserted logging statements in the source code to measure how many times each dependency was established and how many partition instances had been generated during each program execution.

We analyze the situations at the dependency level and the partition instance level as follows.

At the dependency level, for each execution, we collected the dependencies from \( G_P \), and grouped them into five categories by their establishment times (i.e., once, 2 – 9 times, 10 – 99 times, 100 – 999 times, and more than 999 times). We computed a normalized histogram and the total number of dependencies is scaled to 100%.

At the partition instance level, we recorded all the generated partition instances for each execution and grouped them into five categories by the count of equivalent instances. We summed up the total number of partition instances in each category, normalized the histogram on them so that the total number of partition instances is scaled to 100%.

To avoid overloading the readers, for brevity, we only show the results of BFS in Fig. 6. The results of other benchmarks are provided in Appendix I. Fig. 6 shows the normalized histograms at dependency level (left) and at the partition instance level (right) on the BFS benchmark, in which we use different color depths to depict different categories. In each plot, the upper and lower sections show the results from program executions with FAR and Spark\textsubscript{base}, respectively. The program executions resulted in timeout are shown as bars with striped lines. The y-axis is the index of the program execution to obtain the raw data.

In Fig. 6(a), the results show that for all these executions, most dependencies (more than 95%) were established only once. As the execution index increases, more dependencies were involved due to missing partition instances. For the last executions from both FAR and Spark\textsubscript{base}, about 5% of dependencies were established more than once. Only a tiny part (less than 1%) was established more than 999 times in Spark\textsubscript{base}.

However, although the difference is small between FAR and Spark\textsubscript{base} in Fig. 6(a), failure to share partition instances during the establishment of dependencies resulted in performance bloat. Fig. 6(b) summarizes the findings. From the section on FAR, we can see that most partition instances (more than 90%) were grouped under the first category (i.e., each partition was generated only once), and all other partition instances were grouped under the second category (more specifically, each one had less than three equivalent partition instances). From the section on Spark\textsubscript{base}, as the execution index increases, partitions were generated many times and led to a large percentage of all partition instances. In the last row for Spark\textsubscript{base} (before timeout), each partition had more than 999 equivalent partition instances, and accounts for 90% of all instances.

### D. ANSWERING RQ1 THROUGH SCENARIO 2

In Scenario 2, following [26], we measured the \textit{Runtime} spent by each execution as presented in Spark’s Web UI, which is a web interface to monitor and inspect application executions.

Table 3 shows the time spent in each configuration with different fraction of maximum available memory. From the results, when each executor’s memory changed from 8 GB to 5 GB, all program executions for both Spark\textsubscript{base} and FAR finished without experiencing any timeout. Moreover, the differences in time spent between the two techniques are small, indicating that FAR had a comparable performance as Spark\textsubscript{base} under less restrictive memory scenarios in the experiment.

However, as the available memory situation became more stringent, Spark\textsubscript{base} did not continue to scale well and started to perform much poorer than FAR. When the fraction changed from 5 GB to 3 GB, the program executions under Spark\textsubscript{base} started to result in timeout. In contrast, although the time spent incurred by FAR increased by a large margin, program executions still completed before the timeout threshold. In particular, we observed that in the experiment, program
executions on Spark\textsubscript{base} changed from running normally to resulting in a timeout within a change of 1 GB of available memory, whereas execution performance on FAR degraded more gracefully. Finally, for the executions with only 2 GB as the maximum available memory, all the program executions supported by FAR were completed before timeout except for GMM. The overall results indicate that FAR has the potential to complete program executions much earlier than Spark\textsubscript{base} in memory stringent situations.

To further analyze the above program executions, we measured the number of established dependencies and partition instances as what we summarized in Fig. 6. But this time, we only varied the amount of memory assigned to executors across executions. For executions resulted in timeouts (where timeout was set to 3600 seconds as well), we calculated the results of the executions right before timeout. We grouped these partition identifiers into five categories using the same scheme that we used in Fig. 6.

Fig. 7 shows the results of BFS, and the results of other benchmarks are provided in Appendix I.

There are two plots in Fig. 7, in each plot, the upper and lower parts are the executions with FAR and Spark\textsubscript{base}, respectively. From Fig. 7, for program executions which completed successfully using either technique (Spark\textsubscript{base} and FAR), only a small ratio of dependencies had been re-established, and the number of equivalent partition instances were always less than nine.

However, when the available memory became smaller (i.e., less than 4 GB), the program executions using Spark\textsubscript{base} started to result in timeouts. From Fig. 7, the results show that the executions using Spark\textsubscript{base} generated thousands of equivalent instances of some data partitions and these instances took up a very large proportion of all instances generated. As a comparison, with the same memory allocation, each partition instance in program executions using FAR was always associated less than 99 equivalent partition instances. Take BFS with 3 GB memory allocation as an example. Around 60% of all instances using Spark\textsubscript{base} were generated more than 999 times. More specifically, the maximum and mean counts of equivalent partition instances in the fifth category (i.e., larger than 999) were 2049 and 1281. For its counterpart using FAR, the maximum and mean numbers of equivalent partition instances in its third category (i.e., larger than 999) were 20 and 13, respectively. There were two orders of magnitude in difference.

Across all the executions, for both Spark\textsubscript{base} and FAR, the percentage of partition instances in the first category (i.e., generated only once) dropped from around 90% to a small value (less than 20% for FAR, and less than 5% for Spark\textsubscript{base}), which indicates multi-fold increases in the number of equivalent partition instances. The result indicates that these program executions incurred serious re-generation slowdown overheads when the total available memory locations were insufficient to keep all partition instances that these program executions (with their underlying techniques Spark\textsubscript{base} and FAR) aimed to keep at the same time. It also reveals that system deletion of persistent instances has a significant impact on execution slowdowns in this scenario.

### E. Answering RQ2 Through Scenario 3

Similar to the time spent data used in the last subsection, the time spent data in this experiment were extracted from Spark’s Web UI. Table 4 summarizes the mean and standard deviation of the time spent (in seconds) of the program executions using Spark\textsubscript{base} and FAR. The third column shows the ratio of the two columns on its left and the ratio is calculated as mean time spent of FAR ÷ mean time spent of Spark\textsubscript{base}. For this ratio, a value over 1 indicates that FAR is slower than Spark\textsubscript{base}; otherwise, FAR has not been observed to have a disadvantage in terms of the slowdown. To analyze the statistical significance, we also ran one-way ANOVA analysis [37], of which the P-values are shown in the rightmost column.

From the Ratio column, FAR-enabled executions caused slight overheads (0.03% – 1.39%) in three of all the six benchmarks, and speedups (0.45 – 3.51%) for the other three. In terms of statistical significance, all the P-values are larger than 0.05, indicating no significant differences between each two groups of program executions has been found at 5% significance level. Overall speaking, FAR and Spark\textsubscript{base} achieved comparable runtime overheads for all the 240 conducted program executions.

In addition, as Checkpointing is a widely applied fault tolerances strategy to executions, we assessed our approach FAR with checkpointing and found FAR more efficient in handling program executions. More details of the comparison are provided in Appendix II.

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Time Spent (s)</th>
<th>Ratio</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Spark\textsubscript{base}</td>
<td>FAR</td>
<td></td>
</tr>
<tr>
<td>PR</td>
<td>196.2 (4.3)</td>
<td>197.5 (4.8)</td>
<td>1.0066</td>
</tr>
<tr>
<td>WCC</td>
<td>182.9 (5.3)</td>
<td>182.0 (3.7)</td>
<td>0.9954</td>
</tr>
<tr>
<td>SP</td>
<td>164.7 (4.4)</td>
<td>167.0 (3.5)</td>
<td>1.0139</td>
</tr>
<tr>
<td>SVD++</td>
<td>333.7 (22.8)</td>
<td>322.0 (24.3)</td>
<td>0.9649</td>
</tr>
<tr>
<td>GMM</td>
<td>451.5 (11.6)</td>
<td>449.5 (15.4)</td>
<td>0.9955</td>
</tr>
<tr>
<td>BFS</td>
<td>253.0 (6.3)</td>
<td>253.0 (6.7)</td>
<td>1.0003</td>
</tr>
<tr>
<td>Mean</td>
<td>-</td>
<td>-</td>
<td>0.9961</td>
</tr>
</tbody>
</table>

Note: The standard deviation is shown in the parentheses.
F. THREATS TO VALIDITY

The presence of platform bugs remains a major threat of the experiment. FAR needs to calculate accurate dependencies from these activities. Inaccurate results will lead FAR to make wrong decisions on keeping or discarding partition instances. However, as the underlying environment is not guaranteed to be reliable, the completeness of lifecycle activities is not guaranteed either. Although we did not observe that we had encountered this issue in the experiments, it is still possible that FAR may cause memory leak during the execution in other settings.

All the experiments were conducted on the VMware ESXi hypervisor [10]. In general, the virtual machines are isolated and would not interfere with each other. However, when the workload is accidentally high on each and every machine at the same time, there could be preemptions on hardware resources, which yield unstable results. To overcome this threat, we only kept the cluster node virtual machines running during the experiment to avoid the irrelevant workload interfering the experimental results.

The third one lies in the representativeness of the benchmarks. The selected benchmarks used for evaluating FAR have frequent partition operations. Among the six benchmarks, four of them are provided by Spark and widely used in the experiments of prior studies [25], [26]. To obtain greater generalizability, we have searched the open-sourced benchmarks in GitHub, only found two others that incur performance bloat problems are based on iterative algorithms. There were benchmarks but we could not obtain their datasets or these benchmarks could be run on our platforms. However, these benchmarks are all implementations of specific algorithms, different from full-bone industry-strength applications. Readers should interpret our experimental results with care.

The implementation of our technique may contain bugs. We have tested it with small programs and examined the data generated from the benchmarks. We did not observe abnormality.

The experiment was found very time-consuming due to the processing of large datasets and generation of many datasets. Because of the limited resources we can afford, the scale of our experiment could not be scale up further. Within our resource limit, we have evaluated our technique carefully by varying different values for different parameters systematically. Using platforms with other capacity and processing power will certainly give new absolute results. However, we tend to believe that FAR will still outperform Spark$_{base}$ in scenarios incurring performance bloat due to excessive partition instance generation and deletion.

We only used the memory consumptions and execution time as the metrics. Using other metrics may give different results. However, we tend to believe that the performance bloat problem being solved by FAR will still make our technique have a competitive advantage over Spark$_{base}$.

VI. FURTHER DISCUSSIONS

In [2], the authors of Spark$_{base}$ also conducted two experiments to evaluate the performance of Spark$_{base}$ after a node failure and with insufficient memory (i.e., Scenario 1 and Scenario 2 in this work). More specifically, for Scenario 1, they ran 10 iterations of k-means on a 75-node cluster while killing a node at the start of the 6th iteration. Each iteration cost was about 58 seconds except for the 6th iteration, which took 81 seconds as it reconstructed the lost RDD partition instances. For Scenario 2, they ran logistic regression benchmark on 25 machines with varying amounts of data in memory. The results showed that the iteration time increased from 11.5 seconds to 40.7 seconds and 68.8 seconds when 100%, 50% and 0% memory were configured as the storage space.

However, they didn’t encounter severe performance decrease as we had in our experiments. There are two main reasons for this difference. First, both k-means and logistic regression are simple benchmarks that do not create complex lineage graphs. Second, even with complex benchmarks, the issue could be staying unrevealed at an earlier stage of the program execution. In practice, applications are usually complex and long. Enabling FAR under such cases is more necessary and helpful.

In Section V.E, when the available memory is not stringent, the experiment results show that the advantage of FAR is small. However, in practice, there are various use cases that FAR may be applicable. In recent years, deep learning techniques achieved significant advancements. Models with more parameters and more sophisticated structures are proposed and applied to gain insights from massive amounts of data. A lot of work such as SparkNet, TensorflowOnSpark, CaffeOnSpark that integrate the prevalent deep learning libraries together with big data frameworks to enable distributed deep learning executions on Spark and Hadoop clusters [31]–[33]. In these scenarios, these deep learning programs need plenty of memory resources may run together with Spark and lead to dataset deletion problems. It appears to us that FAR has some potential to alleviate the possible dataset re-generation issues.

FAR also provides opportunities to support debugging and testing techniques on Big Data platforms. Mutation testing is an important kind of software testing technique that has been extensively studied in the past decades [30]. During its testing procedure, a set of program variants (called mutants) are generated by seeding small faults in the original program, and then comparisons are made among the original program and these mutants. Given a large number of program mutants and the needs of executing test cases over different program versions, mutation testing is computationally expensive. In addition, execution failures are common in the procedure of mutation testing. In the context of big data programs, these failures may lead to data loss and trigger the retry and recovery mechanism of big data platforms. As we have illustrated in this work, the runtime performance of the re-calculation could be significantly degraded, which makes
mutation testing even harder to be applied. We believe that FAR has the potential to alleviate the situation by effectively identifying, persisting and deleting reusable datasets, which could make mutation testing be conducted more efficiently.

Apricot is a debugging technique for deep learning (DL) models by iteratively conducting weight-adaptation on them [34]. It generates a set of smaller DL models of the original DL model for the purpose of fixing the latter model and uses them in its iterative process to gradually change and re-train the original DL model. We believe that FAR could be applicable in such a scenario if Apricot is run on a Big Data infrastructure, where partitions in FAR are mapped to batches in Apricot.

Compared to Spark\textsubscript{base}, FAR may consume more memory to keep persistent datasets. However, if there is insufficient memory, as in the case of Scenario 2, FAR can still work gracefully. In FAR algorithm, it tracks outstanding uses on each partition in its analysis state, where the algorithm has not been optimized. For instance, deleting a partition with one outstanding use with a smaller ripple effect to re-generate other partitions may be preferable to deleting a partition with more outstanding uses with a larger ripple effect. We leave the investigation of optimizations on FAR as a future work.

VII. RELATED WORK

A. FAULT-TOLERANCE MECHANISMS

There are two major mechanisms for achieving fault-tolerance, lineage graph and checkpointing techniques.

As mentioned in section I, a lineage graph contains RDD instances and the dependency relations between them. If a dataset is missing due to whatever reasons, the information on the graph could be used to recompute the missing dataset to achieve fault-tolerance on data loss [2]. Different from the lineage graph built-in with Spark, FAR takes advantage of dependency relations at both RDD and partition instance levels, which provides finer-grained support. Furthermore, as we analyzed in section III, the hard-coded lineage graph is not always effective to guide the re-computation. By analyzing the execution plan of ongoing action and monitoring the partition instance lifecycle activities, FAR can actively repair the procedure of computations, as well as the whole execution.

There are many checkpointing techniques proposed in the literature [1], [4], [8], [16]–[20]. They periodically back up certain intermediate datasets to secondary storage and can restart the program executions from the saved points. Panda [3] employs the fine-grained checkpointing on the task outputs. It uses the tasks’ intrinsic information, such as the size of output data and the distribution of task runtimes, to dynamically identify tasks to be checkpointed rather than recomputed [3]. Xu et al. proposed a fault-tolerance mechanism for Apache Flink [21]. Their technique injects checkpointing into each iteration and enables checkpointing to be written along with computing RDD values. As the CPU processing could partially overlap the I/O processing, the whole pipeline execution can archive higher efficiency.

We also conducted an exploratory study to assess FAR with the checkpointing approach. The results showed that FAR is more efficient in the comparison experiment. More details are provided in Appendix II.

B. DATASET MANAGEMENT IN DATA PROCESSING

Many existing works seek to find solutions to persistent dataset management for more efficient memory usage as well as better platform optimization [12], [22]–[26]. A major class of them proposes replacement policies for persisted partitions. If the available memory for a later execution is in shortage, such a policy will select and delete part of persisted datasets to release memory locations [27].

Yu et al. proposed a Least Reference Count (LRC) policy to replace the default LRU policy of Spark [26]. LRC exploits the lineage graph and deletes persisted partitions where the corresponding RDD instances have the least numbers of unevaluated children RDD instances. Geng et al. [22] proposed Least Cost Strategy (LCS) which predicts the future usage and recovery cost information of persisted partition instances from their dependency relationships and selectively deletes them.

Spark uses predefined and fixed parameters to reserve datasets for subsequent usage [8]. MemTune dynamically tunes these parameters by exploiting the task scheduling information at runtime to improve the overall memory resource utilization [25]. As Spark allows developers to choose from a few storage levels for RDD dataset storing, Neutrino provides adaptive storage levels and further optimized the memory use [24]. Their adaptive storage levels are chosen based on the access order of RDDs and runtime information [24]. Gounaris et al. investigated the trade-offs between performance and consumed CPU resource of Spark applications. They proposed algorithms to take both execution time and occupied resource into account by dynamically partitioning during the execution [42].

Unlike the techniques in this category, the goal of FAR is not to create a technique to select datasets to be deleted to release memory for other usages. FAR aims to define dataset reuses based on the information of the online lineage graph produced by the Spark platform and the progress of the program execution. Although an important feature of FAR is to delete partitions (if the partition has not been set into some other states by the program execution or the underlying platform) right after all the budgets on the partition instance have been consumed, as discussed in Section VI, FAR has not incorporated strategies to prioritize or select datasets to be deleted in other situations. In fact, unlike strategies like LRC and LCS which do not introduce additional datasets to be persisted, FAR makes retention decisions of partitions and actively changes the states of some partitions to be persistent “for a while”. In this sense, partitions under the management of FAR are still “transient” but last longer than a partition in ephemera state and shorter than a partition in the reserved/persistent state. In the sense of state transition
VIII. CONCLUSION

In this paper, we have proposed FAR, a novel execution repair framework to effectively maintain the partition instance dependencies for Spark program executions. To address the performance bloat problem, FAR provides high-level programming abstraction to help application developers to address the performance problem caused by excessive partition instance generation and deletion. We have presented the novel design and the algorithms of FAR. We have shown its feasibility by implementing it as a component in Spark. We have evaluated it using six benchmarks in different scenarios ranging from execution failures needing re-generation of some partition instances to running programs in environments with stringent available memory constraints. We have evaluated FAR in situations where there are sufficient system resources and there is no failure requiring partition instance re-generation. The results have shown that FAR has the potential to effectively and efficiently address a class of performance bloat in Spark applications. FAR transiently incurs higher memory overheads than Spark due to the needs to keep more persistent partitions temporarily, and the experiment shows that this strategy pays off well. The integrations with other fault tolerance or data management strategies are interesting to be further explored. We leave them as future work.

APPENDIX I

RE-GENERATION HISTOGRAMS OF OTHER FIVE BENCHMARKS IN SCENARIO 1 AND SCENARIO 2

Fig. 8 shows the dependency level and partition instance level histograms of five benchmarks in Scenario 1. We can observe that they followed similar trends as the BFS benchmark in Section V.C. To avoid overloading the readers, we do not repeatedly state similar observations.

Fig. 9 shows the re-generation histograms of five benchmarks in Scenario 2. We notice that SVD++ using Netflix Prize dataset consumed a small amount of memory. Therefore, in this experiment, all the program executions using FAR can complete without experiencing a large increase in execution time. However, under the extreme case with 2 GB memory, the execution using Sparkbase still yielded a large percentage of partition instances and failed to complete before timeout. On GMM, the program execution using FAR resulted in timeout when memory allocation was 2 GB. From Table 3 in Section V.D, GMM’s executions always took longer time than corresponding executions of other benchmarks under the same memory allocations, indicating that GMM was more complex in processing than other benchmarks (which we have inspected the code and confirmed it). However, from Fig. 9, the numbers of partition instances in
program executions using FAR were small (more specifically, no partition had more than 99 instances). We also executed the GMM benchmark under 2 GB available memory without setting any timeout threshold, it took 4552 seconds to complete. This result was 10.0x slower than the corresponding execution with 8 GB available memory, which is comparable with other benchmarks in this aspect. (We could not complete the execution when running on Spark_base after several hours.)

**APPENDIX II**

**FURTHER EXPLORATORY STUDY**

Checkpointing is a widely applied strategy to provide fault tolerance to executions. With checkpointing, an intermediate dataset could be periodically shadowed (i.e., making a copy of the partition instances) even if it has not been persisted by the corresponding program execution. Intuitively, if a failure occurs, the missing partition instances can be retrieved from the snapshot captured via checkpointing.

Although checkpointing is inapplicable to Scenario 2 due to its additional memory overhead in shadowing intermediate datasets, intuitively, it can be applied to Scenario 1 and Scenario 3. We thus ask a question on whether FAR can be at least as good as checkpointing in handling program executions in Scenario 1 and Scenario 3?

To seek the answer to the above question, we implemented the above checkpointing procedure on Spark_base to conduct a further comparison to FAR (and we are unaware of any available checkpointing implementation for Spark yet). We picked PR as the benchmark in this exploratory study. We chose PR as it is representative in all six benchmarks.

Spark provides the checkpoint interface on RDD. When a checkpoint operation is conducted on an RDD instance, the RDD instance is marked for checkpointing. A concrete checkpointing procedure is triggered once an action on such RDD instance is invoked. During checkpointing, the corresponding datasets are generated and saved to non-volatile storage. If a re-generation of the partition instance is needed in a program execution, Spark_base can read the latest snapshot kept in the non-volatile storage during the requested re-generation.

To use checkpointing, we had to modify the source code of the PR benchmark by inserting the checkpoint statements. Specifically, we added code to checkpoint the intermediate RDDs when it finishes its 2nd, 7th, 12th, and 17th iterations. For ease of our discussion, we refer to this implementation as PR_CP. We compared PR_CP with PR using FAR and PR using Spark_base. We measured their time spent in Scenario 1 where an executor was failed at the 3rd, 8th, 13th, 18th, 19th, and 20th iteration as well as their time spent in Scenario 3 (where timeout was set to 3600 seconds as well). We note that PR using Spark_base resulted in timeouts after the 13th iteration.

Fig. 10 summarizes the results of these executions for the three techniques, shown as bars. Along the horizontal axis, the first slot “Start” denotes results of Scenario 3 where these executions run normally. The following slots show the program executions with an executor failed at the 3rd, 8th, 13th, 18th, 19th, and 20th iterations. We note that PR using Spark_base resulted in timeouts after the 13th iteration.

FIGURE 9. Re-generation histograms of executions with different execution memory allocation. In each subfigure, there are four plots for the results of FAR and Spark_base at the dependency level (the first subplot and the second subplot respectively) and at the partition instance level (the third subplot and the fourth subplot respectively).
In these program executions for PRCP, the snapshots were checkpointed at the end of $2^{\text{nd}}$, $7^{\text{th}}$, $12^{\text{th}}$, and $17^{\text{th}}$ iterations. For the program executions that failures occurred at the $3^{\text{rd}}$, $8^{\text{th}}$, $13^{\text{th}}$, and $18^{\text{th}}$ iterations, the recovery to discover the missing partition instances could read directly from the snapshots. On the other hand, for program executions failed at the $19^{\text{th}}$ and $20^{\text{th}}$ iterations, the missing partition instances had to be re-generated by applying transformations on the latest snapshot of the $17^{\text{th}}$ iteration. This setting allows us to evaluate FAR against PRCP in more diverse situations.

Similar to the results presented in the last subsection, the time spent of FAR and that of Sparkbase were similar. However, the time spent of PRCP was almost 4.2x than FAR. We found that the significant difference was due to the need of I/O operations for checkpointing datasets to the non-volatile storage.

We also observe a side effect of using checkpointing interface. Each invocation of checkpointing will break the lineage graph of current execution into disconnected fragments. Because re-generation of partition instances in Sparkbase inherently requires the lineage graph to re-generate partition instances, the remaining fragments can only provide limited visibility on some previously generated instances. Therefore, a program execution might load partition instances from the snapshot without knowing that the equivalent instances might have been currently kept in the memory, which further slowed down the program execution and consumed more memory than expected.

Similar to FAR, PRCP did not introduce additional major runtime overheads when a program execution failed in later concrete execution phases, and yet PRCP spent 3.3x to 3.9x more time than FAR. Given that PRCP needs Sparkbase to support the re-generation of partition instances that are not kept in the snapshot, PRCP can be configured to run with FAR instead of Sparkbase. That is to say, FAR and checkpointing are not competing techniques, rather they are complementary in nature. It also clarifies the nature of FAR that it is not a fault-tolerance technique.

REFERENCES


XIUPFEI MEI received the B.Eng. degree from the School of Computer Science and Engineering, Beihang University (BUAA), China, in 2012. He is currently pursuing the Ph.D. degree in computer science with the City University of Hong Kong. His main research interests include program debugging and analysis in big data platforms, and concurrency bug detection in multi-threaded programs.

HAO ZHANG received the B.Eng. and M.Sc. degrees from Beihang University, China, in 2015 and 2018, respectively. He is currently pursuing the Ph.D. degree in computer science with the City University of Hong Kong. His main research interests include interplay between software engineering and artificial intelligence, as well as program debugging. His work has been reported in ASE and TOSEM.

ZHENGYUAN WEI received the B.Eng. degree (Hons.) in software engineering from the School of Data and Computer Science, Sun Yat-sen University (SYSU), China, in 2017. He is currently pursuing the Ph.D. degree with the Department of Computer Science, City University of Hong Kong. His research interests include deep learning robustness and efficiency, and compiler optimization.

HAIPENG WANG (Graduate Student Member, IEEE) received the B.Eng. degree in software engineering from the Department of Computer Science, Beijing Institute of Technology, and the master’s degree in data engineering from the Department of Computer Science, City University of Hong Kong, where he is currently pursuing the Ph.D. degree. His current research interest includes software engineering in AI.

W. K. CHAN (Member, IEEE) is currently an Associate Professor with the City University of Hong Kong. His research interests include software engineering in general, program analysis and testing for concurrent software and systems, and software infrastructure for AI-based systems. He is currently a Special Issues Editor of Journal of Systems and Software, an Associate Editor of Software Testing, Verification and Reliability, a Review Editor of Array, a Guest Editor of IEEE Transactions on Software Engineering and Methodology (TOSEM), IEEE TRANSACTIONS ON SOFTWARE ENGINEERING (TSE), IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS (TPDS), ACM TRANSACTIONS ON SOCIAL COMPUTING (TSC), TRACONPRACTIONS OF THE ACM (CAME), COMPUTER, ICSE, FSE, ISSTA, ASE, WWW, ICWS, and ICDC.

XIAOXUEN MA received the B.Eng. degree (Hons.) in telecommunication engineering from the College of Physical Science and Technology, Central China Normal University (CCNU), China, in 2017. She is currently pursuing the Ph.D. degree with the Department of Computer Science, City University of Hong Kong. Her current research interest includes dynamic program analysis on concurrency bug detection in multi-threaded programs.

IMRAN ASHRAF received the B.S. degree in computer and information sciences from the Pakistan Institute of Engineering and Applied Sciences (PIEAS), in 2011, with a Gold Medal Award. He is currently pursuing the Ph.D. degree in computer science with the City University of Hong Kong. His current research interests include program analysis and security vulnerability detection in decentralized platforms, such as Ethereum blockchains. His primary research interests include security vulnerability detection techniques are fuzz testing, static analysis, and symbolic execution.