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Lifetime-Based Memory Management for Distributed Data Processing Systems

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ABSTRACT

In-memory caching of intermediate data and eager combining of data in shuffle buffers have been shown to be very effective in minimizing the re-computation and I/O cost in distributed data processing systems like Spark and Flink. However, it has also been widely reported that these techniques would create a large amount of long-living data objects in the heap, which may quickly saturate the garbage collector, especially when handling a large dataset, and hence would limit the scalability of the system. To eliminate this problem, we propose a lifetime-based memory management framework, which, by automatically analyzing the user-defined functions and data types, obtains the expected lifetime of the data objects, and then allocates and releases memory space accordingly to minimize the garbage collection overhead. In particular, we present Deca, a concrete implementation of our proposal on top of Spark, which transparently decomposes and groups objects with similar lifetimes into byte arrays and releases their space altogether when their lifetimes come to an end. An extensive experimental study using both synthetic and real datasets shows that, in comparing to Spark, Deca is able to 1) reduce the garbage collection time by up to 99.9%, 2) to achieve up to 22.7x speed up in terms of execution time in cases without data spilling and 41.6x speedup in cases with data spilling, and 3) to consume up to 46.6% less memory.

1. INTRODUCTION

Distributed data processing systems, such as Spark, process huge volumes of data in a scale-out fashion. Unlike traditional database systems using declarative query languages and relational (or multidimensional) data models, these systems allow users to implement application logics through User Defined Functions (UDFs) and User Defined Types (UDTs) using high-level imperative languages (such as Java, Scala and C# etc.), which can then be automatically parallelized onto a large-scale cluster.

Existing researches in these systems mostly focus on scalability and fault-tolerance issues in a distributed environment. However some recent studies suggest that the execution efficiency of individual tasks in these systems is low. A major reason is that both the heap, which may quickly saturate the garbage collector, and execution frameworks and user programs of these systems are implemented using high-level imperative languages running in managed runtime platforms (such as JVM, .NET CLR, etc.). These managed runtime platforms commonly have built-in automatic memory management, which brings significant memory and CPU overheads. For example, the modern tracing-based garbage collectors (GC) may consume a large amount of CPU cycles to trace living objects in the heap.

Furthermore, to improve the performance of multi-stage and iterative computations, recently developed systems support caching of intermediate data in the main memory and exploit eager combining and aggregating of data in the shuffling phases. These techniques would generate massive long-living data objects in the heap, which usually stay in the memory for a significant portion of the job execution time. However, the unnecessary continuous tracing and marking of such large amount of long-living objects by the GC would consume significant CPU cycles.

In this paper, we argue that distributed data processing systems like Spark, should employ a lifetime-based memory manager, which allocates and releases memory according to the lifetimes of the data objects rather than relying on a conventional tracing-based GC. To verify this concept, we present Deca, an automatic Spark optimizer, which adopts a lifetime-based memory management scheme for efficiently reclaiming memory space. Deca automatically analyzes the lifetimes of objects in different data containers in Spark, such as UDF variables, cached data blocks and shuffle buffers, and then transparently decomposes and stores a massive number of objects with similar lifetimes into a few number of byte arrays. In this way, the massive objects essentially bypass the continuous tracing of the GC and their space can be released by the destruction of the byte arrays.

Last but not the least, Deca automatically transforms the user programs so that the new memory layout is transparent to the users. By using the aforementioned techniques, Deca significantly optimizes the efficiency of Spark’s memory management and at the same time keeps the generality and expressibility provided in Spark’s programming model.

In summary, the main contributions of this paper include:

- We propose a lifetime-based memory management scheme for distributed data processing systems and im-
plement a prototype on top of Spark, which is able to minimize the GC overhead and eliminate the memory bloat problems in Spark.

- We design a method that changes the in-memory representation of the object graph of each data item by discarding all the reference values. The raw data of the fields of primitive types in the object graph will be compactly stored as a byte sequence.

- We propose techniques to group byte sequences of data items with the same lifetime into a few byte arrays, thereby simplifying space reclamation. Deca automatically validates the memory safety of data accessing based on analysis of memory usage of UDT objects.

- We conduct extensive evaluation on various Spark programs using both synthetic and real datasets. The experimental results demonstrate the superiority of our approach by comparing with existing methods.

2. OVERVIEW OF DECA

2.1 Java GC

In typical JVM implementations, a garbage collector (GC) attempts to reclaim memory occupied by objects that will no longer be used. A tracing GC traces which objects are reachable by a sequence of references from some root objects. The unreachable ones, which are called garbages, can be reclaimed. Oracle’s Hotspot JVM implements three GC algorithms. The default Parallel Scavenge (PS) algorithm suspends the application and spawns several parallel GC threads to achieve high throughput. The other two algorithms, namely Concurrent Mark-Sweep (CMS) and Garbage-First (G1), attempt to reduce GC latency by spawning concurrent GC threads that run simultaneously with the application thread.

All the above collectors segregate objects into multiple generations: young generation containing recently-allocated objects, old generation containing older objects, and permanent generation containing class metadata. Based on the assumption that most objects would soon become garbages, a minor GC, which only attempts to reclaim garbages in the young generation, can be run to reclaim enough memory space. However, if there are too many old objects, then a full (or major) GC would be run to reclaim space occupied by the old objects. Usually, a full GC is much more expensive than a minor GC.

2.2 Motivating Example

A major concept of Spark is Resilient Distributed Dataset (RDD), which is a fault-tolerant dataset that can be processed in parallel by a set of UDF operations.

We use Logistic Regression (LR) as an example to motivate and illustrate the optimization techniques adopted in Deca. It is a classifier that attempts to find an optimal hyperplane that separates the data points in a multi-dimensional feature space into two sets. Figure 1 shows the code of LR in Spark. The raw dataset is a text file with each line containing one data point. Hence the first UDF is a map function, which extracts the data points and store them into a set of DenseVector objects and (lines 12–16). An additional LabeledPoint object is created for each data point to package its feature vector and label value together.

```scala
1 class DenseVector[V](val data: Array[V],
2 val offset: Int,
3 val stride: Int,
4 val length: Int) extends Vector[V] {
5 def this(data: Array[V]) =
6 this(data, 0, 1, data.length)
7 ...
8 }
9 class LabeledPoint(var label: Double,
10 var features: Vector[Double]) {
11 def this(data: Array[V]) =
12 this(data, 0, 1, data.length)
13 ...
14 val points = new Array[LabeledPoint](D)
15 ... 16 new LabeledPoint(new DenseVector(features), label)
17 }).cache()
18 var weights =
19 DenseVector.fill(D)(2 * rand.nextDouble - 1)
20 for (i <- 1 to ITERATIONS) {
21 val gradient = points.map { p =>
22 p.features * (1 / (1 +
23 exp(-p.label * weights.dot(p.features))) -
24 1) * p.label
25 }.reduce(_ + _)
26 weights -= gradient
27 }
```

Figure 1: Demo Spark program of Scala LR.

To eliminate disk I/O for the subsequent iterative computation, LR uses the cache operation to cache the resulting LabeledPoint objects in the memory. For a large input dataset, this cache may contain a massive number of objects. After generating a random separating plane (lines 18-19), it iteratively runs another map function and a reduce function to calculate a new gradient (lines 20-26). Here each call of this map function will create a new DenseVector object. These intermediate objects will not be used any more after executing the reduce function. Therefore, if the aforementioned cached data leaves little space in the memory, then GC will be frequently run to reclaim the space occupied by the intermediate objects and make space for newly generated ones. Note that, after running a number of minor GCs, JVM would run a full GC to reclaim spaces occupied by the old objects. However, such highly expensive full GCs would be nearly useless because most cached data objects should not be removed from the memory.

2.3 Life-time based Memory Management

We implement the prototype of Deca based on Spark. In Deca, objects are stored in three types of data containers:
UDF variables, cached RDDs and Shuffle buffers. In each data container, Deca allocates a number of fixed-sized byte arrays. By using the points-to analysis \cite{21}, we map the UDT objects with their appropriate containers. UDT objects are then stored in the byte arrays after eliminating the unnecessary object headers and object references. This compact layout would not only minimize the memory consumption of data objects but also dramatically reduce the overhead of GC, because GC only needs to trace a few byte arrays instead of a huge number of UDT objects. One can see that the size of each byte array should not be too small or too large, otherwise it would incur high GC overheads or large unused memory spaces.

As an example, the LabeledPoint objects in the LR program can be transformed into byte arrays as shown in Figure 2. Here, all the reference variables (in orange color, such as features and data), as well as the headers of all the objects are eliminated. All the cached LabeledPoint objects are stored into byte arrays.

The challenge of employing such a compact layout is that the space allocated to each object is fixed. Therefore, we have to ensure that the size of an object would not exceed its allocated space during execution so that it will not damage the data layout. This is easy for some types of fields, such as primitive types, but less obvious for others. Code analysis is necessary to identify the change patterns of the objects’ sizes. Such an analysis may have a global scope. For example, a global code analysis may identify that the features arrays of all the LabeledPoint objects (created in line 14 in Figure 1) actually have the same fixed size D, which is a global constant. Furthermore, the features field of a LabeledPoint object is only assigned in the LabeledPoint constructor. Therefore, all the LabeledPoint objects actually have the same fixed size. Another interesting pattern is that in Spark applications, objects in cached RDDs or shuffle buffers are often generated sequentially and their sizes will not be changed once they are completely generated. Identifying such useful patterns by a sophisticated code analysis is necessary to ensure the safety of decomposing UDT objects and storing them compactly into byte arrays.

As mentioned earlier, during the execution of programs in a system like Spark, the lifetimes of data containers created by the framework can be pre-determined explicitly. For example, the lifetimes of objects in a cached RDD is determined by the invocations of cache() and unpersist() in the program. Recall that the UDT objects stored in the compact byte arrays would bypass the GC. We put the UDT objects with the same lifetime into the same container. For example, the cached LabeledPoint objects in LR have the same lifetime, so they are stored in the same container. When a container’s lifetime comes to an end, we simply release all the references of the byte arrays in the container, then the GC can reclaim the whole space occupied by the massive amount of objects.

Lastly, Deca modifies the application code by replacing the codes of object creation, field access and UDT methods with new codes that directly write and read the byte arrays.

3. UDT CLASSIFICATION ANALYSIS

3.1 Data-size and Size-type of Objects

To allocate enough memory space for objects, we have to estimate the object sizes and their change patterns during runtime. Due to the complexity of object models, to accurately estimate the size of a UDT, we have to dynamically traverse the runtime object reference graph of each target object and compute the total memory consumption. Such a dynamic analysis is too costly at runtime, especially with a large number of objects. Therefore we opt for static analysis which only uses static object reference graphs and would not incur any runtime overhead. We define the data-size of an object to be the sum of the sizes of the primitive-type fields in its static object reference graph. An object’s data-size is only an upper bound of the actual memory consumption of its raw data, if one considers the cases with object sharing.

To see if UDT objects can be safely decomposed into byte sequences, we should examine how their data-sizes change during runtime. There are two types of UDTs that can meet the safety requirement: 1) the data-sizes of all the instances of the UDT are identical and do not change during runtime; or 2) the data-sizes of all the instances of the UDT do not change during runtime. We call these two kinds of UDTs as Static Fixed-Sized Type (SFST) and Runtime Fixed-Sized Type (RFST) respectively.

In addition, we call UDTs that have type-dependency cycles in their type definition graphs as Recursively-Defined Type. Even without object sharing, the instances of these types can have reference cycles in their object graphs. Therefore, they cannot be safely decomposed. Furthermore, any UDT that does not belong to any of the aforementioned types is called a Variable-Sized Type (VST). Once a VST object is constructed, its data-size may change due to field assignments and method invocations during runtime.

The objective of the UDT classification analysis is to generate the Size-Type of each target UDT according to the above definitions. As demonstrated in Figure 2, Deca decomposes a set of objects into primitive values and stores them contiguously into compact byte sequences in a byte array. A safe decomposition requires that the original UDT objects are either of an SFST or an RFST. Otherwise the operations that expand the byte sequences occupied by an object may overwrite the data of the subsequent objects in the same byte array. Furthermore, as we will discuss later, an SFST can be safely decomposed in more cases than an RFST. On the other hand, objects that do not belong to an SFST or an RFST will not be decomposed into byte sequences in Deca. Apparently, to maximize the effect of our approach, we should avoid overestimating the variability of the data-size of the UDTs, which is the design goal of our following algorithms.

3.2 Local Classification Analysis

The local classification algorithm analyzes an UDT by recursively traversing its type dependency graph. For example, Figure 3 illustrates the type dependency graph of LabeledPoint. The size-type of LabeledPoint can be determined based on the size-type of each of its fields.

Algorithm 1 shows the procedure of the local classification analysis. The input of the algorithm is an annotated type that contains the information of fields and methods of the target UDT. Because the objects referenced by a field can be of any subtype of its declared type, we use a type-set to store all the possible runtime types of each field. The type-set of each field is obtained in a pre-processing phase of Deca by using the points-to analysis \cite{21} (see Section 5).

In lines 1–2, the algorithm first determines whether the
target UDT is a recursively-defined type. It builds the type
dependent graph and searches for cycles in the graph. If a
cycle is found, the algorithm immediately returns recursively-
defined type as the final result.

Two indirect-recursive functions, AnalyzeType (lines 4–
22) and AnalyzeField (lines 23–34), are used to further
determine the size-type of the target UDT. The stop condition
of the recursion is when the current type is a primitive type
(line 5). We treat each array type as having a length field
in its type-set.

We define a total ordering of the variability of the size-
types (except the recursively-defined type) as follows:

SFST $<$ RFST $<$ VST. Based on this order, the size-type
of each UDT is determined by its field that has the highest
variability (lines 12–20). Furthermore, each field’s final size-
type is determined by the type with the highest variability in
its type-set. But a non-final field of an RFST will be finally
classified as VST, because the same field can possibly point
to objects with different data-sizes (lines 28–29). Consider
that whenever we find a VST field, the top-level UDT must
also be classified as a VST. In this case, the function can
immediately returns without further traversing the graph.

We take the type LabeledPoint in Figure 3 as a running example.
In Figure 3, every field has a type-set with a single element and the declared type of each field is equal
to its corresponding runtime type except that the features
field has a declared type (Vector), while its runtime type is
DenseVector. Moreover, for a more sophisticated implementa-
tion of logistic regression with high-dimensional data sets,
the features field can have both DenseVector and
SparseVector in its type-set.

Since there is no cycle in the type dependency graph,
LabeledPoint is not a recursively-defined type. As shown in
Figure 3, LabeledPoint contains a primitive field (i.e. label)
and a field of the Vector type (i.e. features). Therefore, the
size-type of LabeledPoint is determined by the size-type of
features, i.e. the size-type of DenseVector. It contains four:
one of the array type and another three of the primitive
type. The data field will be classified as an RFST but not a
VST due to its final modifier (val in Scala). Furthermore,
the DenseVector objects assigned to features can have dif-
ferent data-size values because they may contain different
arrays. Therefore, both features and LabeledPoint belong
to VST.

3.3 Global Classification Analysis

The local classification algorithm is easy to implement
and has negligible computational overhead. But it is con-
servative and often overestimates the variability of the tar-
get UDT. For example, the local classifier conservatively
assumes that the features field of a LabeledPoint object may
be assigned with DenseVector objects with different data-
size values. Therefore it mistakenly classifies it as a VST,
which can not be safely decomposed.

Furthermore, the local classifier assumes that the
DenseVector objects contain arrays (features.data) with
different lengths. Even if we change the modifier of features
from var to val, i.e. only allowing it to be assigned once, the
local classifier still considers it as an RFST rather than an
SFST.

For UDTs that are categorized as RFST or VST, we fur-
ther propose an algorithm to refine the classification re-
sults via global code analysis on the relevant methods of
the UDTs. To break the assumptions of the local classi-
 fier, the global one uses code analysis to identify init-only
fields and fixed-length array type according to the following
definitions.

Init-only field. A field of a non-primitive type T is init-
only, if, for each object, this field will only be assigned once
during the program execution. 

1We always treat the array element fields as non init-only,
otherwise the analysis needs to trace the element index value
Algorithm 2: Global classification analysis.

Input: The top-level non-primitive type $T$; The locally-classified size-type $S_{local}$; Call graph of the current analysis scope $G_{call}$

Output: The refined size-type of $T$

1. if $S_{local} = StaticFixed$ then return StaticFixed;
2. else if $S_{local} = RuntimeFixed$ or $RRefine(T, G_{call})$ then return RuntimeFixed;
3. else return Variable;

Fixed-length array types. An array type $A$ contained in the type-set of field $f$ is a fixed-length array type w.r.t. $f$ if all the $A$ objects assigned to $f$ are constructed with identical length values within a well-defined scope, such as a single Spark job stage or a specific cached RDD. An example of symbolized constant propagation is shown in Figure 4. Here, array is constructed with the same length for whatever foo() returns. The fixed-length array types with its element fields being SFST (or RFST) can be refined to SFST (or RFST).

```
val a = input.readString().toInt() // a == Symbol(1)
val b = a + 1 // b == Symbol(2)
val c = a * 1 // c == Symbol(1)
if (foo()) array = new Array[Int](b)
else array = new Array[Int](c)
```

Figure 4: Symbolized constant propagation.

In Figure 4, the features field is only assigned in the constructor of LabeledPoint (lines 1–8), and the length of features.data is a global constant value $D$ (lines 14–16). Thus, the size-class of LabeledPoint can be refined to SFST.

Algorithm 3 shows the procedure of the global classification. The input of the algorithm is the target UDT and the call graph of the current analysis scope. The refinement is done based on the following lemmas.

**Lemma 1** (SFST Refinement). An array type that is an RFST or a VST can be refined to an SFST if and only if for every array type in the type dependent graph, the following are true:

1. it is a fixed-length array type; and
2. every type in the type-set of its element field is an SFST.

**Lemma 2** (RFST Refinement). An array type that is a VST can be refined to an RFST if and only if:

1. every type in the type-sets of its fields is either an SFST or an RFST; and
2. each field with an RFST in its type-set is init-only.

The call graph used for the analysis is built in the preprocessing phase (Section 5). The entry node of the call graph is the main method of the current analysis scope, usually a Spark job stage, while all the reachable methods from the entry node as well as their corresponding calling sequences are stored in the graph.

In line 7 of Algorithm 3 we use the following steps to identify the fixed-length array types. (1) Perform the copy-/constant propagation in the call graph. The values passed in each assignment statement, which is not feasible in static code analysis.

Algorithm 3: Static fixed-sized type refinement: SRefine($t_{arg}, g_{arg}$)

```
1 Function SRefine($t_{arg}, g_{arg}$)
Input: A non-primitive type $t_{arg}$; A call graph $g_{arg}$;
Output: true or false that $t_{arg}$’s size-type can be refined to StaticFixed;
2 foreach field $f$ of type $t_{arg}$ do
3   analyze_field $←$ false;
4   foreach runtime type $t$ in $f$.getTypeSet do
5     if $t$ is not a primitive type and not $SRefine(t, g_{arg})$ then return false;
6   end
7   if $t_{arg}$ is an array type and $t_{arg}$ is not Fixed-Length in call graph $g_{arg}$ then return false;
8   else return true;
9 end
```

from the outside of the call graph or returned by the I/O operations will be represented by symbols considered as constant values. (2) For a field $f$ and an array type $A$, find all the allocation sites of the $A$ objects that are assigned to $f$ (i.e. the methods where these objects are created). If all the length values used in all these allocation sites are equivalent, $A$ is of fixed-length w.r.t. $f$.

In line 11 of Algorithm 4, we use the following rules to identify init-only or non-init-only fields: (1) a final field is init-only; 2) an array element field is not init-only; 3) in addition, a field is init-only if it will not be assigned in any method in the call graph other than the constructors of its containing type, and it will only be assigned once in any constructor calling sequence.

**3.4 Phased Refinement**

In a typical data parallel programming framework, such as Spark, each job can be divided into one or more execution phases, each consisting of three steps: (1) reading data from materialized (on-disk or in-memory) data collectors, such as cached RDD, (2) applying an UDF on each data object, and (3) emitting the resulting data into a new materialized data collector. Figure 5 shows the framework of a job in Spark. It consists one or more top-level computation loops, each reads data object from its source, and writes the results.
autoexecbatch

Figure 5: A code template of the Spark job stage.

int into the sink. Every two successive loops are bridged by a
data collector, such as an RDD or a shuffle buffer.

We observe that the data-sizes of object types may have
different levels of variability at different phases. For exam-
ple, in an early phase, data would be grouped together by
their keys and their values would be concatenated into an
array whose type is a VST at this phase. However, once
the resulting objects are emitted to a data collector, e.g. a
cached RDD, the subsequent phases might not reassign the
array fields of these objects. Therefore, the array types can
be considered as RFSTs in the subsequent phases. We ex-
plot this phenomenon to refine a data type’s size-class in
each particular phase of a job, which is called phased refine-
ment. This can be achieved by running the global classifi-
cation algorithm for the VSTs on each phase of the job.

4. LIFETIME-BASED MEMORY MANAGEMENT

4.1 The Spark Programming Framework

Spark provides a functional programming API, through
which users can process Resilient Distributed Datasets
(RDDs), the logical data collections partitioned across a
cluster. An important feature is that RDDs can be explicit-
ly cached in the memory to avoid re-computation or disk
I/O overhead.

While Spark supports many operators, the ones most rel-
ient for memory management are some key-based opera-
tors, including reduceByKey, groupByKey, join and sortByKey
(analogues of GroupBy-Aggregation, GroupBy, Inner-Join
and OrderBy in SQL). These operators process data in the
form of Key-Value pairs. For example, reduceByKey and
groupByKey are used for: 1) aggregating all Values with the
same Key into a single Value; 2) building a complete Value
list for each Key for further processing.

Furthermore, these operators are implemented using data
shuffling. The shuffle buffer stores the combined value of
each Key. For example, for the case of reduceByKey, it stores
a partial aggregate value for each Key, and for the case of
groupByKey, it stores a partial list of Value objects for each
Key. When a new Key-Value pair is put into the shuffle
buffer, eager combining is performed to merge the new Value
with the combined value.

For each Spark application, a driver program negotiates
with the cluster resource manager (e.g. YARN [34]), which
launches executors (each with fixed amount of CPU and
memory resource) on worker machines. An application can
submit multiple jobs. Each job has several stages separated
by data shuffles and each stage consists of a set of tasks that
perform the same computation. Each executor occupies a
JVM process and executes the allocated tasks concurrently
in a number of threads.

4.2 Lifetimes of Data Containers in Spark

In Spark, all objects are allocated in the running execu-
tors’ JVM heaps, and their references are stored in three
kinds of data containers described below. A key challenge
for Deca is deciding when and how to reclaim the allocated
space. In the lifetime analysis, we focus on the end points
of the lifetime of the object references. The lifetime of an
object ends once all its references are dead.

UDF variables. Each task creates function objects accord-
ing to its task descriptor. UDF variables include objects
assigned to the fields of the function objects and the local
variables of their methods. The lifetimes of the function ob-
ject end when the running tasks complete. In addition, as
long-living objects are recommended to be stored in cached
RDDs, in most applications, local variables are dead after
each method invocation. Therefore, we treat all the data
objects referenced only by the local variables as short-living
temporal objects.

Cache blocks. In Spark, each RDD has an object that
records its data source and the computation function. Only
the cached RDDs will be materialized and retained in mem-
ory. A cached RDD consists of a number of cache blocks,
each being an array of objects. The lifetimes of cached RDDs
are explicitly determined by the invocations of cache() and
unpersist() in the applications. Whenever a cached RDD
has been “unpersisted”, all of its cache blocks will be re-
leased immediately. For non-cached RDDs, the objects only
appear as local variables of the corresponding computation
functions and hence are also short-living.

Shuffle buffers. A shuffle buffer is accessed by two succes-
sive phases in a job: one creates the shuffle buffer and puts
data objects into it, while the other reads out the data for
further processing. Once the second phase is completed, the
shuffle buffer will be released.

With regard to the lifetimes of the object references stored
in a shuffle buffer, there are three situations. (1) In a sort-
based shuffle buffer, objects are stored in an in-place sorting
buffer sorted by the Key. Once object references are put
into the buffer, they will not be removed by the subsequent
sorting operations. Therefore, their lifetimes end when the
shuffle buffer is released. (2) In a hash-based shuffle buffer
with a reduceByKey operator, the Key-Value pairs are stored
in an open hash table with the Key object as the hash key.
Each aggregate operation will create a new Value object
while keeping the Key objects intact. Therefore a Value
object reference dies upon an aggregate operation over its
corresponding Key. (3) In a hash-based shuffle buffer with a
groupByKey operator, a hash table stores a set of Key objects
and an array of Value objects for each Key. The combining
function will only append Value objects to the corresponding
array and will not remove any object reference. Hence, the
references will die at the same time as the shuffle buffer.
Note that these situations cover all the key-based operators
in Spark. For example, aggregateByKey and join are similar
4.3 Data Containers in Deca

As discussed above, object references’ lifetimes can be bound with the lifetimes of their containers. Deca builds a data dependent graph for each job stage by points-to analysis [21] to produce the mapping relationships between all the objects and their containers. Objects are identified by either their creation statements if they are created in the current stage, or their source cached blocks if they are read from cached blocks created by the previous stage.

However, an object can be assigned to multiple data containers. For example, if objects are copies between two different cached RDDs, then they can be bound to the cached blocks of both RDDs. In such cases, we assign a sole primary container as the owner of each data object. Other containers are treated as secondary containers. The object ownership is determined based on the following rules:

1. Cached RDDs and shuffle buffers have higher priority of data ownership than UDF variables, simply due to their longer expected lifetimes.

2. If there are objects assigned to multiple high-priority containers in the same job stage, the container created first in the stage execution will own these objects.

In the rest of this subsection, we present how data are organized within the primary and secondary containers under various situations.

4.3.1 Memory Pages in Deca

Deca uses unified byte arrays with a common fixed size as logical memory pages to store the decomposed data objects. A page can be logically split into consecutive byte segments, one for each top-layer object. Each of such segment can be further split into multiple segments, one for each lower-layer object, and so on. The page size is chosen to ensure that there is only a moderate number of pages in each executor’s JVM heap so that the GC overhead is negligible. On the other hand, the page size should not be too large either, so that there would not be a significant unused space in the last page of a container.

For each data container, a group of pages are allocated to store the objects it owns. Deca uses a page-info structure to maintain the metadata of each page group. The page-info of each page graph contains: 1) pages, a page array storing the references of all the allocated pages of this page group; 2) endOffset, an integer storing the start offset of the unused part of the last page in this group; 3) curPage and curOffset, two integer values that store the progress of sequentially scanning, or appending to, this page group.

4.3.2 Primary Container

The way how Deca stores objects in their primary container depends on the type of the container:

**UDF variables.** Deca does not decompose objects owned by UDF variables. These objects do not incur significant GC overheads, because: (1) the objects only referenced by local variables are short-living objects and they belong to the young generation, which will be reclaimed by the cheap minor GCs; (2) the objects referenced by the function object fields may be promoted to the part of old generation, but the total number of these objects in a task is relatively small in comparing to the big input dataset.

**Cache blocks.** Deca always decomposes the SFST or RFST objects and stores their raw data bytes in the page group of a cache block, while keeps the VST objects intact. Figure 6(a) shows the structure of a cache block of a cached RDD, which contains decomposed objects.

A task can read objects from a decomposed cache block created in a previous phase. If this task changes the data sizes of these objects, Deca has to re-construct the objects and release the original page group. To avoid thrashing, when such re-construction happens, Deca will not re-decompose these objects again even if they can be safely decomposed in the subsequent phases.

**Shuffle buffers.** Figure 6(b) shows the structure of a shuffle buffer. Similar to cache blocks, data of an RFST or an SFST in a shuffle buffer will be decomposed into the shuffle buffer’s page group. However, unlike cached RDD, where data are accessed in a sequential manner, data in a shuffle buffer will be randomly accessed to perform sorting or hashing operations. Therefore, as illustrated on the left-hand side of Figure 6(b), we use an array to store the pointers to the keys and values within a page. The hashing and sorting operations are performed on the pointer arrays. However, the pointer array can be avoided for a hash-based shuffle buffer with both the Key and the Value being of primitive types or SFSTs. This is because we can deduce the offsets of the data within the page statically.

As we discussed in Section 4.2 for a hash-based shuffle buffer with a GroupBy-Aggregation computation, a combining operation would kill the old Value object and create a new one. Therefore, Value objects are not long-living and frequent GC of these objects are generally unavoidable. However, if the Value object is of an SFST, then we can still decompose it and whenever a new object is generated by the combining operation, we can just reuse the page segment occupied by the old object, because the old and the new objects are of the same size. Doing this would save the frequent GC caused by these temporary Value objects.

For brevity, we omit swapping data between memory and disks here. It is straightforward to adapt to the cases with disk swapping for data caching and shuffling (see Appendix C for details).

4.3.3 Secondary Container

There are common patterns of multiple data containers sharing the same data objects in Spark programs, such as: 1) manipulating data objects in cache blocks or shuffle buffers through UDF variables; 2) copying objects between cached RDDs; 3) immediately caching the output objects of shuffling; 4) immediately shuffling the objects of a cached RDD.
We implement Deca based on Spark in roughly 6700 lines of Scala code. It consists of an optimizer used in the driver, and a memory manager used in every executor. The memory manager allocates and reclaims memory pages. It works together with the Spark cache manager and shuffle manager, which manage the un-decomposed data objects. The optimizer analyzes and transforms the code of each job when it is submitted in the driver (see Appendix A for details). The transformed code will use the API provided by the memory manager to create pages and access the stored bytes.

The Deca optimizer uses the Soot framework 6 to analyze and manipulate the Java bytecode. The Soot framework provides a rich set of utilities, which implements classical program analysis and optimization methods. The optimization consists of three phases: pre-processing, analysis and transformation.

In the pre-processing phase, Deca uses iterator fusion 27 to bundle the iterative and isolated invocations of UDFs into larger, hopefully optimizable code regions to avoid complex and costly inter-procedural analysis. The per-stage call graphs and per-field type-sets are also built using Soot in this phase. Building per-phase call graphs will be delayed to the analysis phase if a phased refinement is necessary. In the analysis phase, Deca uses methods described in Section 3 and Section 4 to determine whether and how to decompose particular data objects in their containers. Based on the obtained decomposability information, new class files with transformed code will be generated and distributed to all executors in the transformation phase. In general, the accessing of primitive fields of decomposed data objects in the original code will be transformed to accessing the corresponding page segments (see Appendix B for details).

6. EVALUATION

We use five nodes in the experiments, with one node as the master and the rest as workers. Each node is equipped with two eight-core Xeon-2670 CPUs, 64GB memory and one SAS disk, running RedHat Enterprise Linux 5 (kernel 2.6.18) and JDK 1.7.0 (with default GC parameters). We compare the performance of Deca with Spark 1.6. For serializing cached data in Spark, we use Kryo, which is a very efficient serialization framework.

Five typical benchmark applications in Spark are evaluated in these experiments: WordCount (WC), LogisticRegression (LR), KMeans, PageRank (PR), ConnectedComponent (CC). As shown in Table 4 they exhibit different characteristics and hence can verify the system’s performance in various different situations. For WC, we use the datasets produced by Hadoop RandomWriter with different unique key numbers (1M and 100M) and sizes (50GB, 100GB and 150GB). LR and KMeans use: 4096-dimension feature vectors (40GB and 80GB) extracted from Amazon image dataset 24, and randomly generated 10-dimension vectors (ranging from 40GB to 200GB). For PR and CC, we use three real graphs: LiveJournal social network 13 (2GB), webbase-2001 14 (30GB) and a 60GB graph generated by HiBench 3. The maximum JVM heap size of each executor is set to be 30GB for the applications with only data caching or data shuffling, and 20GB for those with both caching and shuffling.

6.1 Impact of Shuffling
WC is a two-stage MapReduce application with data shuffling between the “map” and “reduce” stages. We examine the lifetimes of data objects in the shuffle buffers with the smallest dataset. We periodically record the alive number of objects and the GC time with JProfiler 9.0. The result is shown in Figure 8(a). WC uses a hash-based shuffle buffer to perform eager aggregation, which is implemented in Tuple2. The number of Tuple2 objects, which fluctuates during the execution, can indicate the number of objects in shuffle buffers. While the number of Tuple2 are also large in “map” stage but decrease in shuffle in Deca. GCs are triggered frequently to release the space occupied by the temporary objects in the shuffle buffers.

To avoid such frequent GC operations, Deca reuses the space occupied by the partially-aggregated Value for each Key in the shuffle buffer. Figure 8(b) compare the execution times of Deca and Spark. In all cases, Deca can reduce the execution time by 10%–58%. One could also see that the performance improvement increases with more number of keys. This is because the size of a hash-based shuffle buffer with eager aggregation mainly depends on the number of keys. The reduction of GC overhead would become more prominent with a larger number of keys. Furthermore, since Deca stores the objects in the shuffle buffer as byte arrays, it also saves the cost of data (de-)serialization by directly outputting the raw bytes.

6.2 Impact of Caching

LR and KMeans are representative machine learning applications that perform iterative computations. Both of them first load and cache the training dataset into memory, then iteratively update the model until the pre-defined convergence condition is met. In our experiments, we only run 30 iterations. We do not account for the time to load the training dataset, because the iterative computation dominates the execution time, especially consider that these applications can run up to hundreds of iterations in a production environment. We set 90% of the available memory to be used for data caching.

We first examine the lifetimes of data objects in cache RDDs for LogisticRegression (LR) using the 40GB dataset. The result is shown in Figure 8(a). We find that the number of objects is rather stable throughout the execution in Spark, but full GCs have been triggered several times in vain (the peaks of the GC time curve). This is because most objects are long-living and hence their space cannot be reclaimed. While these objects are less in Deca because they are transformed to bytes after being read from the HDFS. Some objects still live in old generation of JVM heap because no full gc is active.

By grouping massive objects with the same lifetime into a few byte arrays, Deca can effectively eliminate the GC problem of repeatedly scanning alive data objects for their liveness. Figure 9(b) and Figure 9(c) show the execution times of LR and KMeans for both Deca and Spark. Here we also examine the cases using Kryo to serialize the cached data in Spark, which is denoted as “SparkSer” in the figures.

For the 40GB and 60GB datasets, the improvement is moderate and can be mainly attributed to the elimination of object creation and minor GCs. In these cases, the memory is sufficient to store the temporary objects, and hence full GC is rarely triggered. Furthermore, serializing the cached data also helps reducing the GC time. Therefore, with the 40GB dataset, SparkSer outperforms Spark by reducing the GC overhead. However, for larger datasets, the overhead of data (de-)serialization cannot pay off the reduced GC overhead. Therefore, simply serializing the cached data is not a robust solution.

For the three larger datasets the improvement is more significant. The speedups of Deca are ranging from 16x to 41.6x. In these datasets, the long-living objects consume almost all available memory space, and therefore full GCs are frequently triggered, which just repeatedly and unwaveringly trace the cached data objects in the old generation of the JVM heap. With the 100GB and 200GB datasets, the additional disk I/O costs of cache swapping also prolong the execution times of Spark. Deca keeps a smaller memory footprint of cached data and swap smaller portion of data to the disks.

We also conduct the experiments on a real dataset, Amazon image dataset with 4096 dimensions. Figure 9(d) shows the speedups achieved by Deca are ranging from 1.2x to 5.3x. With such a high dimensional dataset, the size of object headers becomes negligible and therefore, the sizes of the cached data of Spark and Deca are nearly identical.

6.3 Impact of Mixed Shuffling and Caching

Table 2: Graph datasets used in PR and CC.

<table>
<thead>
<tr>
<th>Graph</th>
<th>LiveJournal (LJ)</th>
<th>WebBase (WB)</th>
<th>HiBench (HB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vertices</td>
<td>4.8M</td>
<td>118M</td>
<td>602M</td>
</tr>
<tr>
<td>Edges</td>
<td>68M</td>
<td>1B</td>
<td>2B</td>
</tr>
<tr>
<td>Data Size</td>
<td>26GB</td>
<td>30GB</td>
<td>60GB</td>
</tr>
</tbody>
</table>

PageRank (PR) and ConnectedComponent (CC) are representative iterative graph computations. Both of them use groupByKey to transform the edge list to the adjacency lists, and then cache the resulting data. We use three datasets with different edge numbers and vertex numbers as shown in Table 2. We set 40% and 100% of the available heap space for caching and shuffling respectively. Edges will be cached during all iterations, and shuffling is used in every iteration to aggregate messages for each target vertex. We run 10 iterations in all the experiments.
6.4 GC improvement

Table 3 shows the times to run GC and the ratios of GC time to the whole job execution time for the seven applications. For each application, we only present the case with the largest input dataset that does not have data swapping or spilling, to avoid the disk I/O affecting the execution time. For each case, the GC time is an average of the values on all executors. The result demonstrates the effect of GC elimination by Deca, and how it improves the entire application performance. As shown in the result, the GC running time of LR and KMeans occupies the largest portion of the total execution time among all cases, which are 73.4% and 78.9% respectively.

With the 80GB input dataset, the cached data objects almost consume all the memory space of the old generation of the JVM heap. Deca reduces GC running time in two ways: 1) smaller cache datasets trigger much less full GCs; 2) once a full GC is triggered, the overhead of tracing objects is significantly reduced.

Since all the other applications have shuffle phases in their executions, the disk and network I/O account for a significant portion of the total execution time. Furthermore, serving memory spaces for shuffle buffers makes that the long-living cached objects occupy no more than 60% of the total available memory. Therefore, in these cases the GC running time ranges from 64.7% to 69.2%. This explains the different improvement ratios for different types of applications reported above.

We then compare Deca with GC tuning methods. The Spark document [2] states that adjusting the fractions of memory allocated to cache blocks and to shuffle blocks is an effective GC tuning method. Furthermore, we also compare with two GC algorithms available in Hotspot JVM: namely CMS and G1. Table 4 shows the results. LR is very sensitive to GC tuning. By setting fractions of cache and shuffle buffer to 0.6 and 0.4 (the optimal based on our experiments), respectively, or replacing PS with CMS or G1 with tuned parameters, we can significantly improve the performance of LR. However, PR is much less sensitive to GC tunings, which is consistent with the previously reported experiments [4]. However, we cannot achieve the same performance gain by setting a higher number of concurrent GC threads in G1 as reported in [9]. We conjecture that it is because of the difference of the configuration of the machines, which is not stated in [9]. This experiment indicates that GC tuning is an effective way to improve GC performance in some applications, however it is a cumbersome process and is highly dependent on the applications and the system environment.

6.5 Microbenchmark

To make a closer comparison, we attempt to break down
We disable the in-memory compression of Spark SQL.

tables are entirely cached in memory before being queried. For each query, a semantic-identical hand-written Spark program (with RDDs) are used for Spark and Deca. The input dimension is 6.6GB and from the Common Crawl document corpus, where rankings is 6.6GB and uservisits is 4.4GB. We use the table schemas and the two SQL queries provided in Spark’s benchmark [1]. For each query, a semantic-identical hand-written Spark program (with RDDs) are used for Spark and Deca. The input tables are entirely cached in memory before being queried. We disable the in-memory compression of Spark SQL. The first query is a simple filtering:

```
SELECT pageURL, pagerank FROM rankings
WHERE pagerank > 100;
```

The second one is a typical GroupBy aggregate query:

```
SELECT SUBSTR(sourceIP, 1, 5), SUM(adRevenue)
FROM uservisits
GROUP BY SUBSTR(sourceIP, 1, 5);
```

The results are shown in Table 6. All three systems perform equally well for the simple filtering query with small input table. Although the GC running time in Spark is higher than that in the other two systems, it only accounts for a negligible portion of the total execution time. For the second query with a larger table, the GC overhead is significant for Spark. We can see that, similar to Spark SQL, Deca can reduce more than 50% of the execution time in comparing to Spark, while keeping the generality of Spark’s programming framework.
### Table 6: Execution times of two exploratory SQL query in Spark, Spark SQL and Deca. In Query2, the size of swapped cache data in Spark is 23.1GB.

<table>
<thead>
<tr>
<th>Query1</th>
<th>App</th>
<th>exec.</th>
<th>gc</th>
<th>cache</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spark</td>
<td>23s</td>
<td>2.23s</td>
<td>18.6GB</td>
<td>8.6GB</td>
</tr>
<tr>
<td>Spark SQL</td>
<td>22s</td>
<td>0.49s</td>
<td>5.6GB</td>
<td>2.8GB</td>
</tr>
<tr>
<td>Deca</td>
<td>22s</td>
<td>0.26s</td>
<td>23.1GB</td>
<td>2.3GB</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Query2</th>
<th>App</th>
<th>exec.</th>
<th>gc</th>
<th>cache</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spark</td>
<td>396s</td>
<td>192.1s</td>
<td>97.9GB</td>
<td>23.1GB</td>
</tr>
<tr>
<td>Spark SQL</td>
<td>180s</td>
<td>3.08s</td>
<td>47.1GB</td>
<td>9.3GB</td>
</tr>
<tr>
<td>Deca</td>
<td>192s</td>
<td>4.2s</td>
<td>55.6GB</td>
<td>6.3GB</td>
</tr>
</tbody>
</table>

7. RELATED WORK

The inefficiency of memory management in managed runtime platforms for big data processing systems has been widely acknowledged. The existing efforts can be categorized into the following directions.

**GC tuning.** Most traditional GC tuning techniques are proposed for long-running latency sensitive web servers. Some open source distributed NoSQL systems, such as Cassandra [2] and HBase [9], use these latency-centric methods to avoid long GC pauses by replacing the Parallel GC with, e.g., CMS or G1 and tuning their parameters.

**GC algorithms.** Implementing better GC algorithms is another line of work. Maas et al. [23] propose a holistic runtime system for distributed data processing that coordinates the GC executions on all workers to improve the overall job performance. Gidra et al. [19] propose a NUMA-aware garbage collector for data processing running on machines with a large memory space. These approaches’ requirements of modifying JVMs prevent them being adopted on production environments. On the other hand, Deca employs a non-intrusive approach and requires no JVM modification.

**Object serialization.** Many distributed data processing systems, such as Hadoop, Spark and Flink, support serializing in-memory data objects into byte arrays. However, object serialization has long been acknowledged as having a high overhead [16, 25, 26]. Deca transforms the program code to directly access the raw data stored in byte arrays and avoids such overheads.

**Region-based memory management (RBMM).** In RBMM [33], all objects are grouped into a set of hierarchical regions, which are the basic units for space reclamation. The reclamation of a region automatically triggers the recursive reclamation of its sub-regions. This approach requires the developers to explicitly define the mapping from objects to regions, as well as the hierarchical structures of regions. Gog et al. [18] report the early work on using RBMM for distributed data processing that runs on .NET CLR. However, the evaluation is conducted using task emulation with manually implemented operators, while the details about how to transparently integrate RBMM with user codes remain unclear. Nguyen et al. [28] propose an approach that stores all alive objects of user-annotated types in a single region managed by a simplified version of RBMM, thereby bypassing the garbage collection. The occupied space of data objects will be reclaimed at once at a user-annotated reclamation point. This method is unsuitable for systems that create data objects with diverse lifetimes such as Spark. Deca can be regarded as a variant of RBMM, which automatically maps objects with similar lifetimes to the same region.

**Domain specific systems.** Some domain-specific data-

parallel systems make use of its specific computation structure to realize more complex memory management. Since the early adoption of JVM in implementing SQL-based data-intensive systems [30], efforts have been devoted to making use of the well-defined semantics of SQL query operators to improve the memory management performance in managed runtime platforms. Spark SQL [12] transforms relational tables to serialized bytes in a main-memory columnar storage. Tungsten [4], a Spark sub-project, enables the serialization of hash-based shuffle buffers for certain Spark SQL operators. Deca has a similar performance as Spark SQL for structured data processing, meanwhile it provides more flexible computation and data models, which eases the implementation of advanced iterative applications such as machine learning and graph mining algorithms.

8. CONCLUSION

In this paper, we identify that GC overhead in distributed data processing systems is unnecessarily high, especially with a large input dataset. By presenting Deca’s techniques of analyzing the variability of object sizes and safely decomposing objects in different containers, we show that it is possible to develop a general and efficient lifetime-based memory manager for distributed data processing systems to largely eliminate the high GC overhead. The experiment results show that Deca can significantly reduce Spark’s application running time for various cases without losing the generality of its programming framework. Finally, to take advantage of Deca’s optimization, a user is recommended to not creating a massive number of long-living objects of a VST, which cannot be safely decomposed.

9. ACKNOWLEDGMENTS

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10. REFERENCES


APPENDIX

A. HYBRID OPTIMIZATION

Intuitively, Deca can be implemented as a standalone tool that transforms the compiled jar files of a Spark program before its execution. However, a Spark driver program may execute many jobs, each consisting of several stages separated by shuffles. The job submission will be implicitly triggered by an action, such as reduce, which returns a value to the driver after running a UDF on a dataset. According to the results returned by the current job, the driver decides how to submit the next job.

A driver program can freely use the control statements (if/for/while) to control the computation. Therefore, it may submit different jobs with different input datasets and configuration parameters. A static optimization has to enumerate and process all the possible jobs by exhaustively exploring a large number of possible execution paths of the program, which is the well-known path explosion problem. This is even infeasible if the program has loop structures, which render the number of execution paths unbounded.

To address these challenges, we implement Deca in a hybrid way, which contains a static analyzer and a runtime optimizer. The static analyzer extracts priori knowledge about the UDFs and UDTs of the target programs, which can be used to reduce the runtime optimization overheads. The runtime optimizer intercepts the submitted jobs at runtime, and optimizes each job before actually submitting it to the Spark platform. With this approach, Deca only optimizes the actually submitted jobs, and thereby completely eliminates the need for exploring all the execution paths.

B. CODE TRANSFORMATION

In each stage, for the data objects of the UDT that can be safely decomposed, Deca transforms the corresponding code and leaves the unoptimizable parts unchanged. The transformation phase can be further split into three sub-phases, which are described below.

Decomposition. In this sub-phase, Deca generates a synthesized class for each UDT (called SUDT) to access the decomposed raw data. Logically, the reference to a decomposed UDT object will be transformed to the start offset (index of the first byte of its raw data) of its containing byte array. Every field accessing bytecode of this object will be transformed to the array accessing code based on the absolute field offset (object_start_offset + relative_field_offset). The offset computation depends on the raw data size of each UDT instance. In each SUDT, Deca synthesizes static fields or methods to offer data-size values of all the UDT fields. The data sizes of the primitive type fields are already defined in the official JVM specification, while the sizes of non-primitive type fields can be recursively got from the SUDTs of these fields. If a field data-size value can be determined, then it is stored as a global constant value in a static field in the corresponding SUDT. Otherwise, Deca synthesizes a static method of the SUDT to compute the data size during data processing. Similarly, for each UDT, Deca synthesizes static fields or methods to offer relative offset values of all
def computeGradient() = {
  val result = new Array[Double](D)
  var offset = 0
  while(offset < block.size) {
    var factor = 0.0
    val label = block.readDouble(offset)
    offset += 8
    for (i <- 0 to D) {
      val feature = block.readDouble(offset)
      offset += 8
      factor += weights(i) * feature
    }
    factor = (1 / (1 + exp(-label * factor)) - 1) * label
    offset -= 8 * D
    for (i <- 0 to D) {
      val value = block.readDouble(offset)
      offset += 8
      result(i) = result(i) + feature * factor
    }
    offset += 8
  }
  result
}

Figure 12: The transformed code of Logistic Regression.

UDT fields in the SUDT. The relative offsets can be computed based on the field data sizes and the field order in the UDT definition. As an optimization technique, we can reorder the UDT fields by putting the fields with determinable sizes in the front. This method makes more field offset values can be determined by Deca. Once all the field offsets can be computed, Deca transforms every methods of the UDT into its SUDT. During the transformation, all the field accessing code are replaced with the array accessing code.

Linking. Deca only transforms the code of UDTs in the decomposition sub-phase. In this sub-phase, Deca processes the code of UDFs and the main method for each stage. Deca memory manager allocates byte arrays rather than object arrays for data caching and shuffling. In Spark, every task processes data objects sequentially in each UDT object array in a loop. Because the array type is changed, the array index values in the loop must be computed based on the raw data sizes of each object in the optimized code. In fact, the array index variable stores the value of the start offset of the current processing data object. Base on the new array index values, Deca changes the code of UDFs and the main method in the following ways: 1) removes the invocations of UDT object constructors and directly write the initial values in the constructor parameters into the byte arrays based on the absolute field offset; 2) replaces all the field accessing code with the array accessing code; 3) replaces each invocation of a UDT method with the corresponding SUDT method, and adds the byte array and the object start offset as the additional parameters of the invocation.

Optimization. After decomposition and linking, the Deca optimizer further performs classical program optimizations, such as constant/copy propagation, method inlining and loop fusion. Most JVM JIT compilers prefer smaller methods, but we use method inlining aggressively in the pre-processing and transformation phases. If we produce giant methods that have sizes exceeding a threshold value, we split each giant method into several smaller ones using program slicing techniques.

While the code produced by Deca are JVM bytecode, in Figure 12 we provide the equivalent Scala code to illustrate the logic of the transformed LR code. The illustrated part is corresponding to the gradient computation of the original code in line 21-24 of Figure 1.

C. DISK SWAPPING/SPILLING

When the working set size is larger than the available memory space of an executor, Spark moves part of its data out of the memory. For cached RDDs, Spark uses the LRU strategy to select the cache blocks for eviction. The evicted data will be directly discarded or swapped to the local disk according to the user-specified storage-level. For shuffles, Spark always spills the partial data into temporary files, and merges them into final files at the end of task executions.

For cached RDDs, Deca modifies the original LRU strategy to evict page groups rather than cache blocks. Accessing in-page data through either page-infos or pointers will refresh the corresponding page group’s recently-used counter. Spark serializes cache block data before write them into disk files, or transfer them through network for non-local accesses. In Deca, the decomposed data bytes can be directly used for disk and network I/O.

For shuffles, like Spark, Deca sorts the pointers before spilling, and writes the spilled data into files according to the order of the pointers. If a shuffle buffer has only pointers that reference page segments, Deca does not spill these pointers because normally they only occupy a small memory space. It pauses the shuffling and triggers the cache block eviction to make enough room. Deca uses a small memory space (normally only one page) to merge sorted spilled files. Once the merging space is fully filled, the merged data will be flushed to the final output file.