Redundant Loads: A Software Inefficiency Indicator

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Abstract—Modern software packages have become increasingly complex with millions of lines of code and references to many external libraries. Redundant operations are a common performance limiter in these code bases. Missed compiler optimization opportunities, inappropriate data structure and algorithm choices, and developers' inattention to performance are some common reasons for the existence of redundant operations. Developers mainly depend on compilers to eliminate redundant operations. However, compilers' static analysis often misses optimization opportunities due to ambiguities and limited analysis scope; automatic optimizations to algorithmic and data structural problems are out of scope.

We develop LOADSPY, a whole-program profiler to pinpoint redundant *memory load* operations, which are often a symptom of many redundant operations. The strength of LOADSPY exists in identifying and quantifying redundant load operations in programs and associating the redundancies with program execution contexts and scopes to focus developers' attention on problematic code. LOADSPY works on fully optimized binaries, adopts various optimization techniques to reduce its overhead, and provides a rich graphic user interface, which make it a complete developer tool. Applying LOADSPY showed that a large fraction of redundant loads is common in modern software packages despite highest levels of automatic compiler optimizations. Guided by LOADSPY, we optimize several well-known benchmarks and real-world applications, yielding significant speedups.

Index Terms—Whole-program profiling, Software optimization, Performance measurement, Tools.

I. INTRODUCTION

Production software packages have become increasingly complex. They are comprised of a large amount of source code, sophisticated control and data flow, a hierarchy of component libraries, and growing levels of abstractions. This complexity often introduces inefficiencies across the software stacks, leading to resource wastage, performance degradation, and energy dissipation [1], [2]. Such inefficiencies are usually in the form of useless or redundant operations, such as computations whose results may not be used [3], [4], re-computation of already computed values [5], unnecessary data movement [6]–[10], and excessive synchronization [11], [12]. The provenance of these inefficiencies can be many: rigid abstraction boundaries, missed opportunities to optimize common cases, suboptimal algorithm design, inappropriate data structure selection, and poor compiler code generation.

There is a long history of compiler optimizations aimed at statically analyzing and eliminating redundant operations by techniques such as common sub-expression elimination [13], value numbering [14], constant propagation [15], to name a few. However, they have a myopic view of the program, which

limits their analysis to a small scope—individual functions or files. Layers of abstractions, dynamically loaded libraries, multi-lingual components, aggregate types, aliasing, sophisticated flows of control, input-specific path-specific redundancies, and combinatorial explosion of execution paths make it practically impossible for compilers to obtain a holistic view of an application to eliminate all redundancies. Link-time optimization [16] can offer better visibility, however, the analysis is still conservative and may err on the side of being less exhaustive to reduce prohibitive analysis cost. Whole-program link-time optimizations [17], [18] have provided less than 5% average speedup, although a lot more headroom exists as we show in our work. Thus, despite their best efforts, compilers often fall short of eliminating runtime inefficiencies.

Execution profiling aims to understand the runtime behavior of a program. Performance analysis tools such as HPCToolkit [19], VTune [20], perf [21], gprof [22], OProfile [23], and CrayPAT [24] monitor code execution to identify hot code regions, idle CPU cycles, arithmetic intensity, and cache misses, etc. These tools can recognize the utilization (saturation or underutilization) of hardware resources, but they cannot inform whether a resource is being used in a *fruitful* manner that contributes to the overall efficiency of a program. A hotspot need not mean inefficient code, and conversely, the lack of a hotspot need not mean better code. Coarse-grained profilers usually cannot distinguish efficient vs. inefficient code; for example, they cannot identify that repeated memory loads of the same value or result-equivalent computations waste both memory bandwidth and processor functional units.

Whole-program fine-grained monitoring is a means to monitor execution at microscopic details: it monitors each binary instruction instance, including its operator, operands, and runtime values in registers and memory. A key advantage of microscopic program-wide monitoring is that it can identify redundancies irrespective of the user-level program abstractions. Prior work [5], [6], [10], [25] has shown that the fine-grained profiling techniques can identify many forms of software inefficiencies and offer detailed guidance to tune code.

Existing fine-grained profilers pinpoint inefficiencies in a subset of individual operations such as operations with symbolic equivalence [5], dead memory stores [6], and operations writing same values to target registers or memory locations [10]. They have, however, overlooked an important category *temporal load redundancy*—loading the same value from the same memory location. For instance, the code on the left of Listing 1 shows redundant operations that are invisible

Listing 1: An example code (on the left) with temporal inefficiencies that cannot be identified by existing fine-grained profilers. Because arrays A and B are immutable in the loop nest, computing on these loop invariants introduces many redundancies. One can hoist the redundant computation outside of the loop (on the right) for optimization.

Listing 2: An example code (on the left) with spatial inefficiencies that cannot be identified by existing fine-grained profilers. The load redundancy happens at line 4 where the program reads the same value from the nearby memory locations since some adjacent elements of array A have the same value. Such redundancy further results in redundant computation involved in the function func. Because func always returns the same value for the same input. One can compare if the adjacent elements in array A are equivalent to eliminate redundant computation (on the right). If they are the same, one can reuse the return value of func, which is generated in the previous iteration.

in existing fine-grained profilers. In this code, suppose all the scalars are in registers and vectors are in memory. Because there are no "dead store" operations (a store followed by another store to the same location without an intervening load), DeadSpy [6] does not identify any inefficiency. Since the values written in t and delta always change, RedSpy [10] does not report any "silent store" operations [7]. Finally, since there is no symbolic equivalent computation, RVN [5] does not report any inefficiency. Furthermore, because the optimization involves the mathematically equivalent transformation, as shown on the right of Listing 1, it is difficult to optimize with other compiler techniques such as polyhedral optimization [26].

The code on the left of Listing 2 shows another kind of load redundancy, which loads the same value from the *nearby* memory locations. Even though each element of array A is only loaded once, adjacent elements with the same values result in loading the same value and the subsequent redundant computation. We refer to this type of redundancy as *spatial load redundancy*. As a practical example, a sparse matrix with a dense format can yield many spatial load redundancies.

Listing 1 and 2 show a tip of the iceberg of the inefficiencies we target in this paper to complement existing tools. From our observation, a variety of inefficiencies exhibit *substantial* redundant loads; conversely, the presence of a large fraction of redundant loads in an execution is a symptom of some kind of inefficiency *in the code regions* that exhibit such redundancy. Furthermore, the subsequent operations based on redundant loads are potentially redundant.

We have designed and implemented a developer tool—LOADSPY—aimed at profiling an execution and quantifying load redundancy in the execution. LOADSPY highlights precise

source code in its full calling contexts and the two parties involved in a redundant load. Additionally, LOADSPY narrows down the investigation scope to help developers focus on the provenance of inefficiencies. A thorough evaluation on a suite of benchmarks and real-world applications shows that looking for redundant loads in a program offers an easy avenue for performance enhancement in many programs.

In this paper ¹, we make the following contributions:

- Show that redundant loads are a common indicator of various forms of software inefficiencies. This finding serves as the foundation of LOADSPY.
- Describe the design of LOADSPY—a whole-program finegrained profiler to pinpoint redundant loads.
- Develop strategies for analyzing a large volume of profiling data by attributing redundancy to runtime contexts, objects, and scopes.
- Enable rich visualization for a large volume of profiling data coming from different threads/processes with a user-friendly GUI, which improves the usability for non-experts.
- Apply LOADSPY to pinpoint inefficiencies in well-known benchmarks and real-world applications that were the subjects of study and optimization for years and eliminate LOADSPY-found inefficiencies by avoiding redundant loads, which yield nontrivial speedups.

II. RELATED WORK

There exist many compiler techniques and static analysis techniques [13], [28]–[30] to identify redundant computation. However, these static approaches suffer from limitations related to the precision of alias information, optimization scope, and insensitivity to inputs and execution contexts. To address these issues, recent approaches convert the source code to specific notations for redundancy detection and removal [31], or target specific algorithm for optimization [32]. However, these approaches require substantial prior knowledge to identify whether a program suffers from redundancies that are worthy of optimization. In contrast, LOADSPY monitors execution, avoids inaccuracies associated with compile-time analysis, and needs no prior knowledge of the measured programs.

There exist many hardware-based approaches [3], [7], [33]—[38] that optimize redundant operations during program execution. However, these approaches require hardware extension, which is unavailable in commodity processors. Instead, LOADSPY is a pure software approach and does not need any hardware changes. The remaining section reviews only other profiling techniques.

A. Value profiling

LOADSPY is a value-aware profiler; value profiling techniques are closely related to our work. Calder et al. [39]—[41] proposed probably the first value profiler on DEC Alpha processors. They instrumented the program code and recorded top N values to pinpoint invariant or semi-invariant variables stored in registers or memory. A variant of this value profiler

¹This is a full-version of our ICSE paper [27].

was proposed in a later research [42]. Burrows et al. [43] used hardware performance counters to sample values in Digital Continuous Profiling Infrastructure [44]. Wen et al. [45] combined performance monitoring units and debug registers available in x86 to identify redundant memory operations. These approaches do not explore whole-program load redundancy in depth. Moreover, none of them detect spatial redundancy.

Some code specialization work depends on value profiling. However, these approaches limit themselves to only analyzing registers [46], static instructions [47], memory store operations [10], or functions [48]–[50]. They omit many optimization opportunities and require significant manual efforts to reason about the root causes of inefficiencies.

Unlike existing value profilers, LOADSPY has four distinct features. First, LOADSPY is the first value profiler that tracks the *history of loaded values* from individual *memory locations*, rather than the values produced by *individual instructions*. Second, LOADSPY identifies both *temporal and spatial* redundancies in load operations. Third, LOADSPY provides novel redundancy scope and metrics to guide optimization in both contexts and semantics. Fourth, LOADSPY not only identifies redundancy arising due to exactly the same values but also identifies redundancy due to approximately equal values, which offers opportunities for *approximate computing*.

B. Value-agnostic profiling

RVN [5] assigns symbolic values to dynamic instructions and identifies redundancy on the fly. DeadSpy [6] tracks every memory operation to pinpoint a store operation that is not loaded before a subsequent store to the same location. MemoizeIt [51] detects Java methods that perform identical computations. Travioli [52] detects redundant data structure traversals. These approaches miss out on certain opportunities that LOADSPY can detect by explicitly inspecting values generated at runtime.

Toddler [25] has to manually add loop events to instrument loops in a C code base and only identifies repetitive memory loads across loop iterations. The follow-on work LDoctor [53] reduces Toddler's overhead using a combination of ad-hoc sampling and static analysis techniques. LDoctor instruments a small number of suspicious loops at compile time. This technique can miss redundant loads in different loops. In contrast, LOADSPY works on fully optimized binaries, is independent of any compiler, and performs the whole-program profiling instead of limiting itself to only profiling loops.

III. REDUNDANT LOADS: AN INEFFICIENCY SYMPTOM

While there are several ways to identify the inefficiency, LOADSPY focuses on memory load operations. If two consecutive load operations performed on the same memory location load the same value, the second load operation can be deemed useless. Thus, the second load could potentially be elided. Our study aims to quantify redundant loads and attribute them to the code regions that cause them. A single instance of a redundant load is uninteresting; highly frequent redundant loads occurring in the same code location demand attention.

It is easy to imagine how redundant loads happen: repeatedly accessing immutable data structures or algorithms employing memoization. It is equally easy to see how inefficient code sequences show up as redundant loads: missed inlining appears as repeatedly loading the same values in a callee, imperfect alias information shows up as loading the same values from the same location via two different pointers, redundant computations show up as the same computations being performed by loading unchanged values, algorithmic defects, e.g., frequent linear searches or hash collisions, also appear as repeatedly loading unchanged values from the same locations.

Definition 1 (Temporal Load Redundancy). A memory load operation L_2 , loading value V_2 from location M, is redundant if f the previous load operation L_1 , performed on M, loaded a value V_1 and $V_1 = V_2$. If $V_1 \approx V_2$, we call it approximate temporal load redundancy.

Definition 2 (Spatial Load Redundancy). A memory load operation L_2 , loading a value V_2 from location M_2 , is redundant if f the previous load operation L_1 , performed on location M_1 , loaded a value V_1 and $V_1 = V_2$, and M_1 and M_2 belong to the address span of the same data object. If $V_1 \approx V_2$, we call it approximate spatial load redundancy.

Definition 3 (Redundancy Fraction). We define the redundancy fraction \mathcal{R} in an execution as the ratio of bytes redundantly loaded to the total bytes loaded in the entire execution.

We emphasize that the redundancy is defined for instruction instances, *not* static instructions. Deleting an instruction involved in one instance of a redundant load can be unsafe.

Observation 1. Large redundancy fraction (\mathcal{R}) in the execution profile of a program is a symptom of some kind of software inefficiency.

Redundant loads are neither a necessary condition nor a sufficient condition to capture all kinds of software inefficiencies. However, we show, with many illustrative case studies, that a large fraction of redundant loads in the same code region is often a symptom of a serious inefficiency. We notice frequent redundant loads across the board in many programs irrespective of optimization levels, raising a warning alarm of potential inefficiency. Although not all redundant loads demand optimization, in our experience, investigating the top few contributors in a profile offers a high potential to tune and optimize code. Looking for load redundancy opens potentially an easy avenue for code optimization—manual or automatic.

We measure the redundancy fraction in a number of benchmarks SPEC CPU2006 [54], PARSEC-2.1 [55], Rodinia-3.1 [56], and NERSC-8 [57]. We compile these benchmarks with gcc-4.8.5 -03, link-time optimization (LTO) and profile-guided optimization (PGO), which is one of the highest optimization levels. In practice, most packages do not use this level of optimization.

We observe that a large load redundancy fraction correlates with some kind of inefficiency. Furthermore, the code that

Listing 3: Spatial load redundancy in Rodinia-3.1 backprop. Arrays delta and oldw are repeatedly loaded from memory whereas most array elements are zero.

generates many redundant loads is responsible for the inefficiencies in the program. We classify the causes of redundant loads according to their provenance: input-sensitive redundant loads, inefficient data structure/algorithm designs, or missing compiler optimizations. Different kinds of inefficiencies require different optimization strategies.

A. Input-sensitive Redundant Loads

In this section, we classify the inefficiency due to inputs. Rodinia-3.1 backprop [56], a supervised machine learning 10 algorithm, trains the weights of connections in a neural network. The redundancy fraction of this program is 64%. It is common knowledge that as the training progresses, many weights stabilize and do not change. Hence, their gradients become and remain zero. Listing 3 shows the inefficiency at line 3, where the majority of elements in arrays delta and oldw are zeros. Computations at lines 3-5 can be bypassed when delta[j] and oldw[k][j] are zeros. Repeatedly loading the zero value from delta[j] and oldw[k][j] shows up as spatial load redundancy. It is easy to eliminate the input-sensitive redundant loads by predicating the subsequent computation on the values of delta[j] and oldw[k][j] being non-zero.

B. Redundant Loads due to Suboptimal Data Structures and Algorithms

Inefficiencies of this category require semantics to identify and optimize. These inefficiencies also incur a significant number of redundant loads. We illustrate some algorithms that introduce inefficiencies in a few well-known benchmarks.

- a) Linear search: Rodinia-3.1 particlefilter [56] is used to estimate the location of a target object in signal processing and neuroscience. The redundancy fraction of this program is 99%. Listing 4 shows the inefficiency in function findIndex, which performs a linear search (line 3) over a sorted array CDF to determine the location of a given particle. This linear search is called multiple times in a loop to become the bottleneck of the program. The symptom of this inefficiency is many redundant loads, which is caused by the repeated loads of immutable array CDF elements in different invocation instances of function findIndex. To fix this problem, one can replace the linear search with a binary search, which reduces the volume of redundant loads.
- b) Hash table: Parsec-2.1 dedup [55] compresses data via deduplication. The redundancy fraction of this program is 75%. Listing 5 shows the inefficiency in the program, which searches for an item in a linked list associated with a hash table entry. The inefficiency comes from the frequent execution

Listing 4: Temporal load redundancy in Rodinia-3.1 particlefilter. A linear search loads the same values from the same memory locations.

Listing 5: Temporal load redundancy in Parsec-2.1 dedup. Excessive hash collisions in linear hashing result in long linked lists.

on the slow path due to the hash collision. We noticed that only $\sim\!\!2\%$ hash buckets are occupied, and the slow path is frequently taken. The linked list traversal on the slow path loads the same values from the same locations (line 8), which results in redundant loads. One can improve the hash function to make hash keys uniformly distributed among buckets, which will reduce the redundancy and hence the inefficiency.

C. Redundant Loads due to Missing Compiler Optimizations

Inefficiencies of this category occur in small scopes—loop nests or procedure calls. One needs to either curate the code or manually apply transformations to eliminate these inefficiencies. The following three examples illustrate our findings.

- a) Missing scalar replacement: Rodinia-3.1 hotspot 3D [56] is a thermal simulation program that estimates processor temperature. The redundancy fraction of this program is 95%. Listing 6 shows a loop nest that performs a stencil computation. At line 8, tOut_t[c] is updated with the values in nearby $tIn_t[]$. Typically, w = c - 1 and e =c + 1. As a result, the value of tIn_t[e] in the current iteration equals the value of tIn t[c] in the next iteration and further equals the value of tIn t[w] in the iteration after the next. However, the compiler does not perform register promotion of tln_[e]. Hence, many redundant loads occur in this loop nest. To fix this inefficiency, we employ the scalar replacement to eliminate inter-iteration redundant loads from memory. Specifically, we store the value of tIn t[e] in a local variable in the current iteration to be reused by tIn_t[c] in the next iteration and by tIn_t[w] in the iteration after the next.
- b) Missing constant propagation: NERSC-8 ms-grate [57] measures the message passing rate via the MPI interface. The redundancy fraction of this program is 97%. Listing 7 shows a procedure cache_invalidate, which sets all the elements in array cache_buf to 1. This code

```
1 for(y = 0; y < ny; y++) {
2   for(x = 0; x < nx; x++) {
3     int c, w, e, n, s, b, t;
4     c = x + y * nx + z * nx * ny;
5   w = (x == 0) ? c : c - 1;
6   e = (x == nx - 1) ? c : c + 1;
7   ...
8   tOut_t[c] = cc*tIn_t[c]+cw*tIn_t[w]+ce*tIn_t[e]+...
9  }
</pre>
```

Listing 6: Temporal load redundancy in Rodinia-3.1 hotspot3D. Array tIn_t is repeatedly loaded from memory while the values remain unchanged.

Listing 7: Temporal load redundancy in NERSC-8 msgrate. The program repeatedly loads a constant "1" from array cache_buf.

adopts a suboptimal forward propagation that loads the value of <code>cache_buf[i-1]</code> and assigns it to <code>cache_buf[i]</code>. Although there is no redundant load in one invocation of this function, procedure <code>cache_invalidate</code> is called in a loop (not shown in the listing), resulting in excessive, redundant loads from array <code>cache_buf</code>. The compiler does not replace the assignment with a constant, possibly due to its inability to prove the safety of assigning to a global array in the presence of concurrent threads of execution.

- c) Missing inline substitution: SPEC CPU2006 464.h264ref [54] is a reference implementation of H.264, a standard of video compression. The redundancy fraction of this program is 84%. The compiler fails to inline the frequently called function PelYline_11 at line 8 shown in Listing 8. Because it is invoked via a function pointer and the callee routines are not present in the same file. The parameters of PelYline_11—abs_x, img_height, and img_width—are unmodified across multiple successive invocations. In each invocation, the caller pushes the same parameters on the same stack, and then the callee loads the same values from the same location, which show up as redundant loads. To fix the problem, we need to manually inline the function [10].
- d) **Discussion**: We have explored other compiler flags that enable advanced optimization such as polyhedral optimization [58] in GCC. Unfortunately, the polyhedral optimization was unsuccessful in optimizing any of the aforementioned scenarios. Furthermore, we observed that using LTO, PGO, together with the polyhedral optimization made compilation time extremely high for some cases. For example, it took over two hours to compile hotspot 3D, a 30,000× slowdown compared to simply using −03. As a result, our later evaluation section does not use LTO and polyhedral optimization, but only uses −03 with PGO. We leave the effectiveness of other compilers such as LLVM [59] and ICC [60] on the same set of programs for a future study.

Listing 8: Temporal load redundancy in SPEC CPU2006 464.h264ref due to missing function inlining.

IV. LOADSPY IMPLEMENTATION

LOADSPY employs Intel Pin [61] to intercept every memory load operation. The instrumentation obtains the effective address M to be accessed in the instruction, the access length δ , and offers the pair to a runtime analysis routine. In the rest of this section, we discuss how LOADSPY identifies *temporal* and *spatial* load redundancies, respectively.

A. Detecting Temporal Load Redundancy

Detecting temporal load redundancy requires two pieces of information: the current value v_{new} at the target location and the last-time loaded value v_{old} from the same location. The runtime analysis routine, run just before the execution of the original program's load instruction, fetches the current value v_{new} at the memory range $[M:M+\delta)$. LOADSPY employs a shadow memory S for maintaining the last-time loaded value at the same location. S[M] maintains the value last loaded by the program at location M. LOADSPY utilizes the page-table-based scheme [6] to efficiently manage its shadow memory. At runtime, the analysis routine fetches v_{old} from $S[M:M+\delta)$ and v_{new} from $[M:M+\delta)$. LOADSPY records an instance of a *redundant* load if $v_{old} = v_{new}$. All bytes must match to qualify a load as redundant. Intuitively, sub-readsize redundancy is not actionable by the programmer. Note, however, that v_{old} might have been generated by multiple shorter reads, a single longer read, or more commonly a single read of the same size. If not redundant, LOADSPY updates the shadow memory with the newly loaded value. Also, LOADSPY records an instance of a non-redundant load if $v_{old} \neq v_{new}$.

LOADSPY provisions for approximate computation by allowing the new value generated in a floating-point (FP) operation to *approximately* match the previously present value. If the two values are within a threshold of difference, LOADSPY considers them approximately equal and records an instance of a redundant load. The threshold is tunable; we use 1% in our experiments. Accordingly, LOADSPY decomposes the load redundancy into *precise* and *approximate*.

LOADSPY attributes each instance of redundant loads (and non-redundant loads) to two parties $\langle C_{old}, C_{new} \rangle$ involved in two operations, where C_{old} is the calling context of the previous load operation on M and C_{new} is the calling context of the current load operation on M.

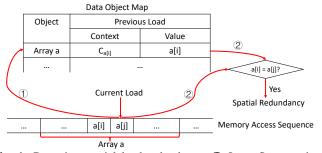


Fig. 1: Detecting spatial load redundancy. ① LOADSPY monitors a load operation and associate its effective address with the data object. In a map, each data object associates itself with the value and context of the previous load belonging to this data object. ② LOADSPY compares the previous and current load values; if they are (approximately) the same, an instance of (approximate) spatial load redundancy is reported. ③ The value and context associated with the data object are updated with the ones from the current load.

The following equations compute the fraction of temporal load redundancy in an execution:

$$\mathcal{R}_{prog}^{precise} = \frac{\sum_{i} \sum_{j} \text{Redundant non-FP bytes loaded in } \langle C_{i}, C_{j} \rangle}{\sum_{i} \sum_{j} \text{non-FP bytes loaded in } \langle C_{i}, C_{j} \rangle}$$

$$\mathcal{R}_{prog}^{approx} = \frac{\sum_{i} \sum_{j} \text{Redundant FP bytes loaded in } \langle C_{i}, C_{j} \rangle}{\sum_{i} \sum_{j} \text{FP bytes loaded in } \langle C_{i}, C_{j} \rangle}$$

$$(1)$$

Load redundancy between a pair of calling contexts is given by the following equations:

$$\mathcal{R}^{precise}_{\langle C_{old}, C_{new} \rangle} = \frac{\text{Redundant non-FP bytes loaded in } \langle C_{old}, C_{new} \rangle}{\sum_{i} \sum_{j} \text{non-FP bytes loaded in } \langle C_{i}, C_{j} \rangle}$$

$$\mathcal{R}^{approx}_{\langle C_{old}, C_{new} \rangle} = \frac{\text{Redundant FP bytes loaded in } \langle C_{old}, C_{new} \rangle}{\sum_{i} \sum_{j} \text{FP bytes loaded in } \langle C_{i}, C_{j} \rangle}$$

$$(2)$$

The metrics help identify code regions (pairs of calling contexts) where the highest amount of redundancy is observed.

Obtaining the Runtime Calling Context of an Instruction: Attributing runtime statistics to a flat profile (just an pointer) does not offer full insights instruction developers. For example, attributing redundant loads to a common library function, e.g., strcmp, offers little insight since strcmp can be invoked from several places in a large code base; some invocations may not even be obvious to the user code. A detailed attribution demands associating profiles to the full calling context: main():line->A():line->...->strcmp():line. LOADSPY requires obtaining the calling context on each load operation since each load—redundant or not. LOADSPY employs CCTLib [62], which efficiently maintains calling contexts as a calling context tree (CCT) [63] including complex control flows through longjump, tail calls, and exceptions. The calling context, which is provided as a unique 32-bit integer, is recorded (in addition to the last-time loaded value) in the shadow memory.

B. Detecting Spatial Load Redundancy

For arrays and aggregate objects, LOADSPY checks whether two consecutive loads from any element of the same object load (approximately) the same value. For example, if two consecutive loads from an array a, say a[i] and a[j], load the same value, LOADSPY flags it as an instance of *spatial*

load redundancy and attributes it to the same data object, as shown in Figure 1.

To facilitate spatial load redundancy detection, LOADSPY maintains a mapping from address ranges to active data objects in a shadow memory. Associated with each data object \mathcal{O} is two additional pieces of information: a singleton value v_{old} loaded as a result of the previous load operation performed on \mathcal{O} and the calling context C_{old} associated with the previous load operation performed on \mathcal{O} . Upon each memory load, LOADSPY uses the effective address of the load operation to look up the data object it belongs to in the map. If the value of the current load matches the one recorded with the previous load on the same object, LOADSPY records an instance of spatial load redundancy. The redundancy is hierarchically attributed first to the data object involved and then to the two calling contexts involved in the redundancy.

LOADSPY provides the similar whole-program and perredundancy-pair metrics for spatial redundancy. Moreover, LOADSPY computes the per-data-object metrics with the following equations where \mathcal{O} is a data object.

$$\mathcal{R}_{\mathcal{O}}^{precise} = \frac{\text{Redundant non-FP bytes in object } \mathcal{O}}{\sum_{i} \text{non-FP bytes in object } i}$$

$$\mathcal{R}_{\mathcal{O}}^{approx} = \frac{\text{Redundant FP bytes in object } \mathcal{O}}{\sum_{i} \text{FP bytes in object } i}$$
(3)

Obtaining Data-object Addresses at Runtime: LOADSPY monitors static and dynamic data objects but ignores stack objects from spatial redundancy detection. Data allocated in the .bss section in a load module are static objects. Each static object has a named entry in the symbol table that identifies the memory range for the object with an offset from the beginning of the load module. The lifetime of static objects begins when the enclosing load module (executable or dynamic library) is loaded into memory and ends when the load module is unloaded. LOADSPY intercepts the loading and unloading of load modules to monitor the lifetime of static data objects and establishes a mapping from an object's address range to the corresponding data object.

Dynamic objects are allocated via one of malloc family of functions (malloc, calloc, realloc) and mmap [64]. The memories for dynamic objects are reclaimed at free and munmap. LOADSPY intercepts these functions to establish a mapping from an object's address range to the corresponding data object. Querying an address at runtime obtains a handle to the corresponding static or dynamic object. The handle is a unique identifier representing the object name for a static object or the allocation calling context for a dynamic object.

C. Identifying the Redundancy Scope

When the redundancy happens in the same calling context, that is $C_{old} = C_{new}$, there is guaranteed to be a loop 2 around the redundancy location. However, in code with nested loops, it is unclear whether the redundancy occurred between iterations of an inner loop or between iterations of an outer loop or some other loop in-between. Hence, it becomes necessary to point out the syntactic scope enclosing a redundancy pair.

²We consider natural loops [65] only.

```
1 <u>do</u> 500 k=1, k1
 1 \underline{do} 500 k=1, kl
                                         scalar = x(ixs)
                                        do iii = ixs, ixl-1
 3
     xx=x0-deltt*(cgx+ux(ia,ic)
                                    3
          )/rslat(ic)*180./pi
                                           if(xx >= scalar) then
 4
                                             scalar = x(iii+1)
    do iii = ixs, ix1-1
                                             if (xx <= scalar)</pre>
 6
       \underline{if}(xx \ge x(iii) .and. xx 7
                                                ixx = iii; exit
            \leq x(iii+1)) then
                                             endif
                                    9
                                           else scalar = x(iii+1)
         ixx = iii; exit
       endif
                                    10
                                           endif
    enddo
                                    11
                                        enddo
10
                                    12
11 500 continue
                                    13 500 continue
```

Listing 9: A code example (on the left) from MASNUM-2.2 [66] that requires additional information for disambiguating the scope of load redundancy. Many redundant loads occur at line 6 where the array x is repeatedly loaded from memory. If we only focus on the inner loop, we would be misled to believe the stencil computation, which loads x(iii+1) and x(iii), causes many redundant loads across iterations of the inner loop. However, performing scalar replacement (on the right) does not yield much speedup. An algorithmic-level redundancy happens in the outer do loop, which repeatedly performs linear searches for a sorted array of elements.

We illustrate the need for scope using a real-world application MASNUM-2.2 [66] shown on the left of Listing 9. LOADSPY identifies 91% of memory loads are redundant and the top contributor is at line 6. It is tempting to infer that x (iii+1) loaded in one iteration of the inner do loop (line 5) is loaded again as x (iii) in the next iteration. An obvious optimization is to perform scalar replacement to retain x (iii+1) across iterations of the inner do loop (on the right of Listing 9). However, this optimization does not eliminate many redundant loads. Actually, the outer do loop at line 1 repeatedly searches for an item xx, and the inner do loop performs a linear search. As a result, the inner loop repeatedly loads the same set of elements across two trips of the outer loop. Thus, the load redundancy exists not only between iterations of the inner loop but also between iterations of the outer loop. The load redundancy at the outer loop highlights an algorithm-level inefficiency—repeated linear searches. With this knowledge, we can replace the linear search with a binary search. More details are shown in § VII-B.

To assist developers to focus on the *scope* where load redundancy occurs, we have incorporated a *redundancy scope* feature in LOADSPY. We denote redundancy scope with the symbol \mathcal{S} . In Listing 9, the redundancy scope is the *outer* do loop. Below we detail how redundancy scope is computed.

We first extend calling contexts to incorporate loop information. Thus, the calling context of a load operation looks as follows: $main() \rightarrow loop_1 \rightarrow f() \rightarrow ... \rightarrow loop_n \rightarrow load_{old}.$ Additionally, LOADSPY maintains a 64-bit global timestamp counter $\mathcal T$ that is incremented when passing through each loop header and also through each load operation. Thus, the calling context snapshot may appear as follows: $C_{old} = main() \rightarrow loop_1[\mathcal T=1] \rightarrow f() \rightarrow ... \rightarrow loop_n[\mathcal T=9] \rightarrow load_{old}.$ We extend the calling context E to be a tuple, that is, $E_{old} = \langle pointer\ to\ old\ context, \mathcal T_{old} \rangle = \langle C_{old}, 10 \rangle.$

Listing 10 shows a simplified example, where the redundancy happens in the inner loop (scope is $loop_2$). In this

Listing 10: Redundancy in the Listing 11: Redundancy in the inner loop scope.

setting, consider the following pair of calling context snapshot:

```
E_{old} = \langle main() \rightarrow loop_1[\mathcal{T} = 1] \rightarrow loop_2[\mathcal{T} = 2] \rightarrow load_{old}, \mathcal{T}_{old} = 3 \rangle
E_{new} = \langle main() \rightarrow loop_1[\mathcal{T} = 1] \rightarrow loop_2[\mathcal{T} = 4] \rightarrow load_{new}, \mathcal{T}_{new} = 5 \rangle
```

Notice that the counter associated with $loop_1$ has remained unchanged whereas the counter associated with $loop_2$ has changed. Each load maintains a *pointer* to the calling context, not the entire calling context snapshot. Hence, by the time the redundancy is detected, that is, $load_{new}$ is executed, $loop_2[\mathcal{T}=2]$ would have gotten updated to $loop_2[\mathcal{T}=4]$; traversing C_{old} would find $\mathcal{T}_{loop_2}=4$. Observe that $\mathcal{T}_{old}<\mathcal{T}_{loop_2}<\mathcal{T}_{new}$. This invariant informs that $loop_2$ is the scope inside which the redundancy is happening. The same invariant does not hold for \mathcal{T}_{loop_1} .

Now, consider a simplified example in Listing 11, where redundancy happens in the outer loop (scope is $loop_1$). In this setting, consider the following pair of calling context snapshot:

```
\begin{split} E_{old} = & (main() \rightarrow loop_1[\mathcal{T}=1] \rightarrow loop_2[\mathcal{T}=2] \rightarrow load_{old}, \mathcal{T}_{old} = 3 \rangle \\ E_{new} = & (main() \rightarrow loop_1[\mathcal{T}=8] \rightarrow loop_2[\mathcal{T}=9] \rightarrow load_{new}, \mathcal{T}_{new} = 10 ) \end{split}
```

Notice that the counter associated with both $loop_1$ and $loop_2$ have changed. Hence, by the time $load_{new}$ is executed, $loop_1[\mathcal{T}=1]$ and $loop_2[\mathcal{T}=2]$ would have gotten updated to $loop_1[\mathcal{T}=8]$ and $loop_2[\mathcal{T}=9]$, respectively; traversing C_{old} would find $\mathcal{T}_{loop_1}=8$ and $\mathcal{T}_{loop_2}=9$. Observe that $\mathcal{T}_{old}<\mathcal{T}_{loop_1}<\mathcal{T}_{loop_2}<\mathcal{T}_{new}$. The loop with the smallest \mathcal{T} value obeying this invariant, that is $loop_1$, is the redundancy scope. If there was another enclosing loop, say $loop_0$, its counter would not have obeyed this invariant.

pair Claim 1. Given redundancy context $\langle \langle C, \mathcal{T}_{old} \rangle, \langle C, \mathcal{T}_{new} \rangle \rangle$, the redundancy \mathcal{S} scope is the outermost enclosing loop i in Cthat $\mathcal{T}_{old} < \mathcal{T}_{loop_i} < \mathcal{T}_{new}$.

Proof. First, \mathcal{T}_{loop_i} must be in the range of $(\mathcal{T}_{old}, \mathcal{T}_{new})$ because loop i is the redundancy scope; otherwise, loop i cannot enclose the redundant load instances. Next, assume there exists another loop j in C such that $\mathcal{T}_{old} < \mathcal{T}_{loop_j} < \mathcal{T}_{loop_i} < \mathcal{T}_{new}$ but loop j is not the redundancy scope. Loop i and j cannot be the peer loops because they are both in the same context C. Then one loop must enclose the other. (1) If loop i encloses loop j, $\mathcal{T}_{loop_i} < \mathcal{T}_{loop_j}$ because loop j's counter is incremented at least once after loop i's counter is incremented, which contradicts the assumption that $\mathcal{T}_{loop_j} < \mathcal{T}_{loop_i}$. Hence, loop j cannot be nested inside loop i. (2) If loop j encloses loop i, then loop i is no longer the outermost loop with $\mathcal{T}_{old} < \mathcal{T}_{loop_i} < \mathcal{T}_{new}$. Hence, loop j cannot be enclosing loop i. Since loop i and loop j are neither peer loops, nor

can they be nested within one another, the assumption is void. Thus, Claim 1 holds.

Implementing Redundancy Scope: LOADSPY combines static and dynamic analysis to compute the redundancy scope S for each redundancy pair. First, LOADSPY instruments each loop header in the binary (in addition to procedures) to produce calling contexts with augmented loop information. It identifies an instruction as a loop header by performing an interval analysis [67] on the binary code and integrates the information into the procedure call path. We refer to the calling contexts with loop information as extended contexts. A runtime analysis routine run as a part of each loop header increments the 64-bit timestamp counter \mathcal{T} . The analysis routine run as a part of each load instruction also increments the counter \mathcal{T} . Also, the shadow memory for each byte of the original program is extended to hold the counter \mathcal{T} (in addition to the 32-bit calling context handle and the 8-bit old value).

On each detected load redundancy, where $C_{old} = C_{new}$, LOADSPY searches the call path from root (main) toward the leaf (the load instruction) to look for the first loop node where the Claim 1 is found to be true. Such a loop is the redundancy scope $\mathcal S$ for the current instance of load redundancy. Each redundancy instance records the triplet $\langle C_{old}, C_{new}, \mathcal S \rangle$. If $C_{old} \neq C_{new}$, LOADSPY first finds the lowest common ancestor (LCA) function or loop enclosing C_{old} and C_{new} , and then searches their common call path from root (main) toward the LCA to obtain $\mathcal S$ based on the Claim 1.

Computing the redundancy scope for each redundancy instance introduces heavy runtime overhead. We compute the redundancy scope for a given calling context pair only a threshold number of times (one in our experiments), which is good enough for most programs.

D. Handling Threaded Programs

LOADSPY maintains per-thread data structures: calling context trees, redundancy profiles, \mathcal{T} , among others and hence needs no concurrency control for multi-threaded programs. The runtime object map is maintained as a lock-free map allowing concurrent lookups. LOADSPY detects only intrathread redundancy and ignores inter-thread redundancy, if any.

E. Reducing Profiling Overhead

LOADSPY can introduce relatively high runtime overhead, ~40-150×. LOADSPY adopts a bursty sampling mechanism to control its overhead [68]. Bursty sampling involves continuous monitoring for a certain number of instructions (WINDOW_ENABLE) followed by not monitoring for a certain (larger) number of instructions (WINDOW_DISABLE) and repeating it over time. These two thresholds are tunable. From our experiments, 1% sampling rate with WINDOW_ENABLE=1 million and WINDOW_DISABLE=99 million yields a good tradeoff between overhead and accuracy.

F. Discussions

It is worth noting that there is no one-one relationship between the redundancy fraction and potential performance gains because of pipelining, caching and prefetching in hardware. LOADSPY does not distinguish actionable vs. non-actionable redundancies, which is a topic of our future work.

V. LOADSPY WORKFLOW

LOADSPY consists of three components: a runtime profiler (detailed previously in § IV), an analyzer, and a GUI. LOADSPY accepts fully optimized binary executables and collects runtime profiles via its online profiler. The analyzer and GUI, run in a postmortem fashion, consume the runtime profiles and associate them with the application source code. The rest of this section discusses the analyzer and GUI.

A. LOADSPY's Analyzer

LOADSPY's analyzer associates the runtime profiles with source code based on the DWARF [69] information produced by compilers. As the profiler produces per-thread profiles, the analyzer needs to coalesce the profiles for the whole execution. The calling context profiles scale the analysis of program execution to a large number of cores. The coalescing procedure follows the rule: two redundancy pairs from different threads are merged iff they have the same redundant loads in the same contexts with the same redundancy scope. All the metrics are also merged to compute unified ones across threads. The scheme is similar for profiles from different processes.

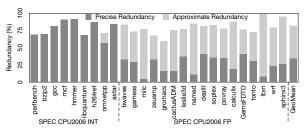
It is worth noting that the profile coalescing overhead grows linearly with the number of threads and processes used by the monitored program. LOADSPY leverages the reduction tree technique [70] to parallelize the merging process. Typically, LOADSPY takes less than one minute to produce the aggregate profiles in all of our case studies.

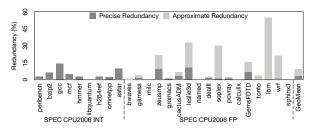
B. LOADSPY's GUI

LOADSPY's GUI inherits the design of an existing Javabased graphical interface [19], which enables navigating the calling contexts and the corresponding source code ordered by the monitored metrics. A top-down view shows a call path C starting from main to a leaf function with the breakdown of metrics at each level. Merely attributing a metric to two independent contexts loses the association between two related contexts during postmortem inspection. To correlate the source with the target, LOADSPY allows appending a copy of the target calling context to the source calling context. For example, if a load in context main->A->B is redundant with another load in context main->C->D, LOADSPY constructs a synthetic calling context: main->A->B->main->C->D. The redundancy metrics will be attributed to the leaf of this call chain. These synthetic call chains make it easy to visually navigate profiles and focus on top redundancy pairs. Figure 4 in § VII-A shows an example of the GUI, and we postpone the explanation of the GUI details to that section.

VI. EVALUATION

We evaluate LOADSPY on a 12-core Intel Xeon E5-2650 v4 CPU (Broadwell) of 2.20GHz frequency running Linux 4.8.0. The machine has 256GB main memory. We evaluate LOADSPY with well-known benchmarks, such as SPEC





(a) Temporal redundancies. (b) Spatial redundancies.

Fig. 2: Fraction of temporal and spatial load redundancies on SPEC CPU2006.

CPU2006 [54], SPEC OMP2012 [71], SPEC CPU2017 [72], Parsec-2.1 [55], Rodinia-3.1 [56], NERSC-8 [57], and Stamp-0.9.10 [73], as well as several real-world applications, such as Apache Avro-1.8.2 [74], Hoard-3.12 [75], MASNUM-2.2 [66], Shogun-6.0 [76], USQCD Chroma-3.43 [77], Stack RNN [78], Binutils-2.27 [79], and Kallisto-0.43 [80]. All the programs are compiled with gcc-4.8.5 -03 PGO except Hoard-3.12 and MASNUM-2.2. For Hoard-3.12 we use clang-5.0.0 -03 PGO and for MASNUM-2.2 we use icc-17.0.4 -03 PGO. We apply the ref inputs for SPEC CPU2006, OMP2012 and CPU2017 benchmarks, the native inputs for Parsec-2.1 benchmarks, and the default inputs released with the remaining benchmarks and applications if not specified. We run all the parallel programs with four threads with simultaneous multi-threading (SMT) disabled.

In the rest of this section, we first show the fraction of temporal and spatial redundancies obtained from SPEC CPU2006. We then evaluate the accuracy and overhead of LOADSPY with bursty sampling enabled. We exclude three benchmarks—gobmk, sjeng, and xalancbmk—from monitoring because they have deep call recursion causing LOADSPY to run out of memory.

- a) Load redundancy in macro benchmarks: Figure 2 shows the fraction of temporal and spatial load redundancies on SPEC CPU2006. We can see (1) load redundancy, especially the temporal one, pervasively exists and (2) integer benchmarks show a high proportion of precise redundant loads whereas floating-point benchmarks show a high proportion of approximate redundant loads, as expected.
- b) Accuracy: LOADSPY offers bursty sampling as an optional feature for users willing to tradeoff measurement accuracy with performance. Figure 3 evaluates the accuracy of LOADSPY with bursty sampling enabled. The geo-means of spatial load redundancy fractions LOADSPY measures with sampling enabled and disabled are nearly the same—10%. The geo-means of temporal load redundancy fractions LOADSPY measures with sampling enabled and disabled are similar—76% and 82%. However, libquantum is an outlier, whose temporal redundancy fractions are 15% and 68% with sampling enabled and disabled. With further investigation, we find that the average number of instructions executed between the source and target load operations of most redundancy pairs is more than 10 million, which is greater than the default WINDOW_ENABLE (= 1 million). In such a case,

	Detecting Temporal Redundancy		Detecting Spatial Redundancy		
Benchmarks	Runtime Slowdown	Memory Bloat	Runtime Slowdown	Memory Bloat	
perlbench	38×	11×	51×	7×	
bzip2	13×	2×	13×	1.09×	
gcc	19×	26×	19×	25×	
mcf	6×	14×	6×	1.04×	
hmmer	12×	35×	11×	20×	
libquantum	12×	18×	13×	2×	
h264ref	21×	20×	21×	2×	
omnetpp	10×	16×	14×	25×	
astar	11×	13×	11×	18×	
bwaves	17×	14×	15×	1.16×	
gamess	24×	25×	24×	24×	
milc	4×	10×	4×	1.18×	
zeusmp	8×	14×	7×	1.42×	
gromacs	10×	23×	9×	15×	
cactusADM	7×	10×	7×	1.36×	
leslie3d	9×	10×	8×	2×	
named	10×	11×	10×	9×	
dealII	21×	30×	22×	19×	
soplex	13×	13×	13×	2×	
povray	29×	216×	28×	70×	
calculix	21×	18×	20×	19×	
GemsFDTD	8×	14×	8×	1.42×	
tonto	22×	49×	24×	30×	
lbm	4×	14×	3×	1.15×	
wrf	15×	10×	16×	3×	
sphinx3	13×	16×	13×	7×	
Median	12.5×	14×	13×	5×	
GeoMean	13×	17×	13×	5×	

TABLE I: LOADSPY's runtime slowdown and memory bloat over native execution on SPEC CPU2006.

one can enlarge WINDOW_ENABLE to improve the accuracy. For instance, when we set WINDOW_ENABLE = 10 million and 50 million (WINDOW_DISABLE remains unchanged), the temporal load redundancy fraction of libquantum increases to 30% and 60%, respectively.

c) Overhead: Table I shows the runtime slowdown and memory bloat of LOADSPY on SPEC CPU2006. The runtime slowdown (memory bloat) is measured as the ratio of the runtime (peak memory usage) of a benchmark with LOADSPY enabled to the runtime (peak memory usage) of its native execution. The geo-means of runtime slowdown for detecting temporal and spatial redundancies are both 13×, and the geomeans of memory bloat for detecting temporal and spatial redundancies are 17× and 5×, respectively. A few benchmarks such as tonto and povray show excessive memory bloat due to the following reasons: (1) tonto has a deep call stack, which demands excessive space to maintain its calling context tree and (2) povray has a small (~6MB) memory footprint, whereas some preallocated data structures in LOADSPY overshadow this baseline memory footprint.

VII. CASE STUDIES

We evaluate the load redundancies found in some benchmarks and real-world applications. Table II summarizes the inefficiencies found and the speedups obtained by eliminating them. We quantify the performance of all programs in execution time except Hoard in throughput. In the rest of this

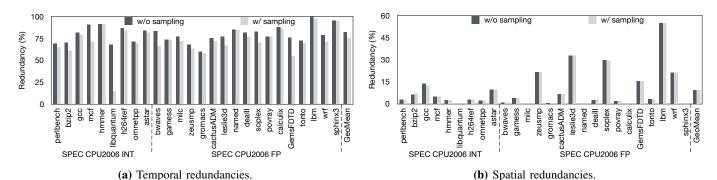


Fig. 3: Comparing temporal and spatial load redundancies with bursty sampling disabled and enabled. The sampling rate is 1%.

Program Information		LOADSPY		Optimization		
Programs Problematic Code		Redundancy Types	Inefficiencies	Approaches	WS*	
Macro Benchmarks	359.botsspar	sparselu.c:loop(191)	Temporal	Inefficient register usage	Scalar replacement	1.77×
	453.povray	csg.cpp(250)	Temporal	Missing inline substitution	Function inlining	1.05×
	464.h264ref	mv-search.c:loop(394)	Temporal	Missing inline substitution	Function inlining	1.28×
	✓470.lbm	lbm.c:LBM_performStreamCollide	Spatial	Redundant computation	Approximate computing	1.25×
	✓538.imagick_r	morphology.c:loop(2982)	Spatial	Redundant computation	Conditional computation	1.25×
	√backprop	backprop.c:loop(322)	Spatial	Input-sensitive redundancy	Conditional computation	1.13×
	✓hotspot3D	3D.c:loop(98, 166)	Temporal	Inefficient register usage	Scalar replacement	1.13×
	√lavaMD	kernel_cpu.c(175)	Temporal	Redundant function calls	Reusing the previous result	1.39×
	✓srad_v1	main.c:loop(256)	Temporal	Inefficient register usage	Scalar replacement	1.11×
	✓srad_v2	srad.cpp:loop(131)	Temporal	Inefficient register usage	Scalar replacement	1.12×
	√particlefilter	ex_particle_OPENMP_seq.c:findIndex	Temporal	Linear search	Binary search	9.8×
	vacation	client.c:loop(198)	Temporal	Redundant function calls	Reusing the previous result	1.23×
	dedup	hashtable.c:hashtable_search	Temporal	Poor hashing	Reducing hash collisions	1.11×
	msgrate	msgrate.c:cache_invalidate	Temporal	Missing constant propagation	Copy propagation	3.03×
Real Applications	✓Apache Avro-1.8.2	Specific.hh(110, 117)	Temporal	Missing inline substitution	Function inlining	1.19×
	✓Hoard-3.12	libhoard.cpp:xxmalloc	Temporal	Redundant computation	Reusing the previous result	1.14×
	✓MASNUM-2.2	propagat.inc:loop(130, 140)	Temporal	Linear search	Locality-friendly search	1.79×
	✓USQCD Chroma-3.43	qdp_random.h(56)	Temporal	Missing inline substitution	Function inlining	1.06×
	✓Shogun-6.0	DenseFeatures.cpp(505) Distance.cpp(185)	Temporal	Missing inline substitution	Function inlining	1.06×
	✓Stack RNN	StackRNN.h:loop(350, 355, 363, 367)	Temporal	Poor choice of algorithm	Loop fusion	1.09×
			Spatial	Redundant computation	Conditional computation	
	Kallisto-0.43	KmerHashTable.h(131)	Temporal	Poor hashing	Reducing hash collisions	4.1×
	Binutils-2.27	dwarf2.c:loop(2166)	Temporal	Linear search	Binary search	3.29×

√: newfound performance bugs via LOADSPY.

WS*: whole-program speedup after problem elimination

TABLE II: Overview of performance improvement guided by LOADSPY.

section, we exhaustively analyze all the newfound performance bugs.

A. Apache Avro-1.8.2

Avro [74] is a remote procedure call (RPC) and data serialization processing system. We apply LOADSPY to evaluate the C++ version of Avro with benchmarks developed by Sorokin [81]. LOADSPY reports a temporal redundancy fraction $\mathcal{R}_{prog}^{precise}$ of 79% for the entire program. Figure 4 shows the full calling contexts of the top redundancy pair visualized through LOADSPY's GUI. LOADSPY's GUI consists of three panes: the top pane shows the program source code, the bottom left pane shows the full calling contexts of each redundancy pair, and the bottom right pane shows the metrics associated with each redundancy pair. In this figure, the GUI shows two metrics: the number of redundant loads for a given redundancy pair and percentage of redundant instances for a given pair, which if 100%, means every instance of this pair is redundant.

From the figure, we can see that the redundant loads in function doEncodeLong account for 25% of the total redundant loads in the program. Moreover, all instances of this pair are redundant. The redundancy scope of this pair is the loop at lines 229-233 in the file Specific.hh enclosing the

call site of function <code>encode</code>. Function <code>encode</code> is the caller of function <code>doEncodeLong</code>. With further analysis, we find that the epilog of function <code>doEncodeLong</code> consistently pops the same values from the same stack location to restore the register values. To eliminate redundant loads in the function epilog, we inline <code>doEncodeLong</code> into its caller. <code>LOADSPY</code> further identifies another problematic function (not shown) and guides the same inlining optimization. Together, these optimizations eliminate 31% of the memory loads and 37% of the redundant memory loads, yielding a 1.19× speedup for the whole program.

B. MASNUM-2.2

MASNUM [66], one of the 2016 ACM Gordon Bell Prize finalists, forecasts ocean surface waves and climate change. It is written in Fortran and parallelized with MPI. LOADSPY identifies 91% of memory loads are redundant, of which 15% are attributed to the array x at line 6 on the left of Listing 9. LOADSPY also pinpoints the redundancy scope as the outermost loop at line 1. We find that the innermost loop (line 5) performs a linear search over the non-decreasing array x for a given input xx. With multiple iterations, elements of array x are frequently loaded from memory for comparison, leading to

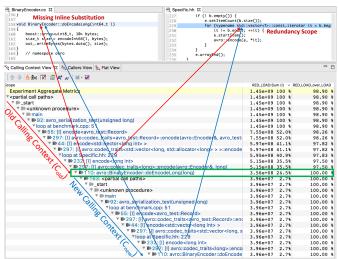


Fig. 4: The top redundancy pair in Avro with full calling contexts reported by LOADSPY. Along the calling contexts shown in the 1 to bottom left pane, a procedure name following a symbol [I] means 2 it is inlined. We can see that most procedures on the path are inlined, except doEncodeLong. Many redundant loads are from calling doEncodeLong, which can be removed by function inlining.

the redundancy. Changing the linear search to a binary search reduces redundant loads and yields a $1.32\times$ speedup for the entire program. It is worth noting that the binary search still incurs high load redundancy fraction because of the intensive search requests in the program. To further improve the search algorithm, we analyze the values of xx across iterations. We find that xx has good value locality, that is, the values are similar in adjacent iterations of the outermost loop. Thus, we replace the binary search with a locality-friendly search. We memoize the location index iii when the current search finishes; in the next search, we begin at the recorded iii and alternate the linear search in both directions to the array start and end. This optimization eliminates 33% of the memory loads and 36% of the redundant memory loads, yielding a $1.79\times$ speedup for the entire program.

C. Hoard-3.12

Hoard [75], a high-performance cross-platform C++ based memory allocator, has been integrated into an array of applications and programming languages such as GNU Bayonne and Cilk programming language. It has 20K lines of code and is parallelized with the PThreads library. LOADSPY identifies that 58% of memory loads are redundant on profiling Hoard's built-in benchmark larson. The top redundancy pair is associated with lines 4 and 7 shown in Listing 12, which accounts for 11% of the total redundant loads. The cause of such redundancy is that the program repeatedly checks whether theTLAB is a null pointer. More specifically, function isCustomHeapInitialized at line 15 and function getCustomHeap at line 16 both include code to check whether theTLAB is equal to nullptr. Hence, the second check at lines 8-11 in getCustomHeap is redundant.

To eliminate such redundant loads, we inline these two functions into their caller xxmalloc and remove the redundant

```
1 static __thread TheCustomHeapType * theTLAB
       INITIAL_EXEC_ATTR = nullptr;
 3 bool isCustomHeapInitialized() {
    return (theTLAB != nullptr);
 6 TheCustomHeapType * getCustomHeap() {
    auto tlab = theTLAB;
    if (tlab == nullptr)
      tlab = initializeCustomHeap();
10
      theTLAB = tlab;
11
12
    return tlab;
13 }
14 void
       * xxmalloc (size t sz) {
    if (isCustomHeapInitialized()) {
15
     void * ptr = getCustomHeap()->malloc(sz);
16
17
18
19 }
```

Listing 12: Temporal load redundancy in Hoard-3.12. The program repeatedly checks whether the pointer variable theTLAB is null.

Listing 13: Temporal load redundancy in USQCD Chroma-3.43. The epilog of function sranf often pops the same values from the same stack location to restore the register values.

check. This optimization eliminates 3% of the memory loads and 2% of the redundant memory loads, which improves the throughput (i.e., the number of memory operations per second) of Hoard by $1.14\times$.

D. USQCD Chroma-3.43

Chroma [77] is a complex toolbox for performing quantum chromodynamics lattice computations, which has more than 200K lines of code. We evaluate it using the built-in benchmark t_mesplq. LOADSPY reports a temporal redundancy fraction of 61%. The top redundancy pair is attributed to the function sranf at line 3 shown in Listing 13. With further investigation, we notice that Chroma has a similar performance bug to the one in Apache Avro: the epilog of function sranf repeatedly pops the same values from the same stack location to restore the register values.

To eliminate such redundant loads, we manually inline the callee into its caller. This optimization eliminates 6% of the memory loads and 7% of the redundant memory loads, yielding a $1.06\times$ speedup for the whole program.

E. Shogun-6.0

Shogun [76] efficient machine learning toolbox. LOADSPY reports a temporal redundancy fraction of 71% on profiling its built-in benchmark kernel_matrix_sum_benchmark. Listing 14 shows one of the top redundancy pairs at line 6. The cause of such redundancy is similar to Apache Avro: the epilog of function get_feature_vector repeatedly pops the same values from the same stack location to restore the register values. We manually inline the callee into its caller

Listing 14: Temporal load redundancy in Shogun-6.0. The epilog of function get_feature_vector often pops the same values from the same stack location to restore the register values.

to eliminate these redundant loads. Additionally, We perform $^{10}_{11}$ the same optimization for other function invocations that have the same performance issue. These optimizations eliminate 12 7% of the memory loads and 2% of the redundant memory 13 loads, yielding a $1.06\times$ speedup for the whole program.

F. Stack RNN

Stack RNN [78] is a C++ based project originating from Facebook AI research, which applies memory stack to optimize and extend a recurrent neural network. We evaluate Stack RNN by profiling its built-in application train_add with LOADSPY. LOADSPY quantifies a redundancy fraction of 81%, and pinpoints that the top temporal and spatial load redundancy pairs are associated with four loops shown in Listing 15.

The cause of the temporal load redundancy is that each of the four loops accesses array <code>_err_stack</code>. However, the compiler cannot keep all elements of array <code>_err_stack</code> in CPU registers across these loops. Thus, the elements of array <code>_err_stack</code> are repeatedly loaded from memory into registers. We eliminate the temporal redundant loads by loop fusion, which fuses the four loops into one so that array <code>_err_stack</code> is only loaded once.

The cause of the spatial load redundancy is that most elements of array _err_stack are zeros, resulting in identity computation at lines 2, 5, 9 and 12 shown in Listing 15. We employ a conditional check to avoid the computation on identities. These two optimizations together eliminate 10% of the memory loads and 15% of the redundant memory loads, yielding a 1.09× speedup for the whole program.

G. SPEC CPU2006 470.lbm

470.lbm [54] employs the lattice boltzmann method to simulate incompressible fluids in three-dimensional space. LOADSPY reports that spatial redundant loads account for 55% of the total memory loads, of which more than 30% are attributed to the array srcGrid at lines 11-54 shown in Listing 16. With further investigation, we find that array srcGrid is traversed across loop iterations and most of its elements are identical, resulting in many redundant loads.

To optimize this inefficiency, we apply loop perforation [82] to reduce the number of iterations at the cost of accuracy. With this optimization, the memory loads and redundant memory loads are reduced by 26% and 60%, and the whole program gains a $1.25 \times$ with trivial accuracy loss (7.7e-5%).

```
1 for (my_int i = _TOP_OF_STACK; i < _TOP_OF_STACK +</pre>
      _STACK_SIZE - 1; i++) {
    _pred_err_stack[s][i+1] += _err_stack[s][i] * _act[s][itm
      ] [pop];
4 for (my_int i = _TOP_OF_STACK; i < _TOP_OF_STACK +
       _STACK_SIZE - 1; i++) {
    _err_act[s][pop] += _err_stack[s][i] * _stack[s][old_it][
7_err_act[s][pop] += _err_stack[s][_TOP_OF_STACK +
       _STACK_SIZE - 1] * EMPTY_STACK_VALUE;
8 for (my_int i = _TOP_OF_STACK + 1; i < _TOP_OF_STACK +</pre>
       _STACK_SIZE; i++) {
    _pred_err_stack[s][i-1] += _err_stack[s][i] * _act[s][itm
       ][push];
10
   for (my_int i = _TOP_OF_STACK + 1; i < _TOP_OF_STACK +</pre>
        _STACK_SIZE; i++) {
    _err_act[s][push] += _err_stack[s][i] * _stack[s][old_it
      ][i-1];
```

Listing 15: Temporal and spatial load redundancies in Stack RNN. Array _err_stack is loaded from memory by each of the four loops, resulting in temporal load redundancy. Besides, most elements of array _err_stack equal zero, resulting in spatial load redundancy.

H. SPEC CPU2017 538.imagick_r

538.imagick_r [72] is applied to create, edit, compose or convert bitmap images. LOADSPY reports that spatial redundant loads account for 13% of the total memory loads, of which 24% are attributed to the variable k at lines 6-9 shown in Listing 17. k is a pointer to the floating-point array values at line 2 and decrements by one in each iteration. We find that most elements of this array equal zero, causing *k to equal zero in most of loop iterations.

To remove the identity computation on $\star k$, we introduce a conditional check to filter out all zero values. With this optimization, the memory loads and redundant memory loads are reduced by 19% and 51%, and the whole program achieves a $1.25 \times$ speedup.

I. Rodinia-3.1 Srad

Srad [56] applies partial differential equations to filter noise in images, which is widely used in ultrasonic and radar imaging applications. We profile the OpenMP version of srad_v1. LOADSPY reports a temporal redundancy fraction of 99%. 8% of the redundancy is attributed to the array image at lines 12-14 shown in Listing 18. We notice that when 0 < i < Nr - 1, the value of image[iS[i] + Nr*j] in one iteration equals the value of image[k] in the next iteration and further equals the value of image[iN[i] + Nr*j] in the iteration after next.

To fix this problem, we adopt scalar replacement to avoid redundant loads across iterations, which eliminates 33% of the memory loads and yields a $1.11\times$ speedup for the whole program. It is worth noting that the indirect accesses in this inefficient code snippet introduce challenges in compiler's static analysis and optimization.

```
1 #define SWEEP_START(x1,y1,z1,x2,y2,z2) \
i < CALC_INDEX(x2, y2, z2, 0); \
 4 i += N_CELL_ENTRIES ) {
 5 #define SWEEP_END }
 7 static double srcGrid[SIZE_Z*SIZE_Y*SIZE_X*N_CELL_ENTRIES];
 9 SWEEP_START( 0, 0, 0, 0, 0, SIZE_Z ) // loop entry
10 ...
11 \blacktriangleright rho = + SRC_C ( srcGrid ) + SRC_N ( srcGrid )
12 ▶ + SRC_S ( srcGrid ) + SRC_E ( srcGrid )
13 \triangleright + SRC_W ( srcGrid ) + SRC_T ( srcGrid )
14 ▶ + SRC_B ( srcGrid ) + SRC_NE( srcGrid )
15 ▶ + SRC_NW( srcGrid ) + SRC_SE( srcGrid )
16 ▶ + SRC_SW( srcGrid ) + SRC_NT( srcGrid )
17 ▶ + SRC_NB( srcGrid ) + SRC_ST( srcGrid )
18 ▶ + SRC_SB( srcGrid ) + SRC_ET( srcGrid )
19 ▶ + SRC_EB( srcGrid ) + SRC_WT( srcGrid )
20 ▶ + SRC_WB( srcGrid );
21 ▶ ux = + SRC E ( srcGrid ) - SRC W ( srcGrid )
22 ▶ + SRC_NE( srcGrid ) - SRC_NW( srcGrid )
23 ▶ + SRC_SE( srcGrid ) - SRC_SW( srcGrid )
24 \blacktriangleright + SRC_ET( srcGrid ) + SRC_EB( srcGrid )
25 \blacktriangleright -SRC_WT( srcGrid ) - SRC_WB( srcGrid );
26 \blacktriangleright uy = + SRC_N ( srcGrid ) - SRC_S ( srcGrid )
27 \blacktriangleright + SRC_NE( srcGrid ) + SRC_NW( srcGrid )
28 ➤ - SRC SE( srcGrid ) - SRC SW( srcGrid )
29 \blacktriangleright + SRC_NT( srcGrid ) + SRC_NB( srcGrid ) 30 \blacktriangleright - SRC_ST( srcGrid ) - SRC_SB( srcGrid );
31 \blacktriangleright \text{uz} = + \text{SRC\_T} ( srcGrid ) - SRC_B ( srcGrid )
32 ▶ + SRC_NT( srcGrid ) - SRC_NB( srcGrid )
33 ▶ + SRC_ST( srcGrid ) - SRC_SB( srcGrid )
34 ▶ + SRC_ET( srcGrid ) - SRC_EB( srcGrid )
35 \blacktriangleright + SRC_WT( srcGrid ) - SRC_WB( srcGrid );
36 . . .
37 \triangleright DST_C ( dstGrid ) = (1.0-OMEGA)*SRC_C ( srcGrid ) + ...
38 \blacktriangleright DST_N ( dstGrid ) = (1.0-OMEGA)*SRC_N ( srcGrid ) + ...
39 \triangleright DST_E ( dstGrid ) = (1.0-OMEGA)*SRC_E ( srcGrid ) + ...
40 \triangleright \text{DST\_W} ( dstGrid ) = (1.0-OMEGA)*SRC_W ( srcGrid ) +
41 \triangleright DST_T ( dstGrid ) = (1.0-OMEGA)*SRC_T ( srcGrid ) + ...
42 \triangleright DST_B ( dstGrid ) = (1.0-OMEGA)*SRC_B ( srcGrid ) + ...
43 ► DST_NE( dstGrid ) = (1.0-OMEGA) *SRC_NE( srcGrid ) + ...
44 ▶ DST_NW( dstGrid ) = (1.0-OMEGA)*SRC_NW( srcGrid ) + ...
45 \triangleright DST\_SE(dstGrid) = (1.0-OMEGA)*SRC\_SE(srcGrid) +
46 ▶ DST_SW( dstGrid ) = (1.0-OMEGA)*SRC_SW( srcGrid ) + ...
47 \triangleright DST_NT( dstGrid ) = (1.0-OMEGA)*SRC_NT( srcGrid ) + ...
48 ▶ DST_NB( dstGrid ) = (1.0-OMEGA) *SRC_NB( srcGrid )
49 \triangleright DST_ST(dstGrid) = (1.0-OMEGA)*SRC_ST(srcGrid) +
50 \triangleright DST\_SB(dstGrid) = (1.0-OMEGA)*SRC\_SB(srcGrid)
                                                                  . . .
51 \triangleright DST\_ET( dstGrid ) = (1.0-OMEGA)*SRC\_ET( srcGrid )
                          = (1.0-OMEGA) *SRC_EB( srcGrid ) + ...
52 ► DST_EB( dstGrid )
53 ► DST_WT( dstGrid ) = (1.0-OMEGA) *SRC_WT( srcGrid ) +
54 \triangleright DST_WB(dstGrid) = (1.0-OMEGA)*SRC_WB(srcGrid) + ...
56 \, \text{SWEEP\_END} \, // \, \text{loop exit}
```

Listing 16: Spatial load redundancy in SPEC CPU2006 470.lbm. Array srcGrid is frequently loaded from memory while most array elements have the same values.

Additionally, LOADSPY also identifies the same inefficiency occurring in srad_v2. With the same optimization, srad_v2 achieves a 1.12× speedup.

J. Rodinia-3.1 LavaMD

LavaMD [56] calculates particle potential and relocation among particles. We apply LOADSPY to evaluate its OpenMP version. LOADSPY reports that 87% of memory loads are redundant, and the top contributor is the glibc function exp at line 7 shown in Listing 19. We notice that the value of u2 often remains unchanged across iterations. As a result, a number of redundant loads and computations occur inside exp due to redundant function calls. With further analysis, we find

```
1 register const double *restrict k;
2 k = &kernel->values[kernel->width*kernel->height-1]
3 ...
4 for (u=0; u < (ssize_t) kernel->width; u++, k--) {
5   if (IsNaN(*k)) continue;
6  result.red += (*k)*k_pixels[u].red;
7  result.green += (*k)*k_pixels[u].green;
8  result.blue += (*k)*k_pixels[u].blue;
9  result.opacity += (*k)*k_pixels[u].opacity;
10  ...
11 }
```

Listing 17: Spatial load redundancy in SPEC CPU2017 538.imagick_r. Array values is frequently loaded from memory. However, most array elements equal zero.

```
1 for (i=0; i<Nr; i++) {</pre>
2
   iN[i] = i-1;
   iS[i] = i+1;
3
4 }
6 iN[0]
          = 0;
7 is[Nr-1] = Nr-1;
9 for (j=0; j<Nc; j++) {
   for (i=0; i<Nr; i++) {
10
11
      k = i + Nr*j;
12 ▶
      Jc = image[k];
13 ▶
      dN[k] = image[iN[i] + Nr*j] - Jc;
      dS[k] = image[iS[i] + Nr*j] - Jc;
15
```

Listing 18: Temporal load redundancy in Rodinia-3.1 srad_v1. Array image is repeatedly loaded from memory while the values remain unchanged.

that a2 is a loop invariant, and u2 is derived from a2 and r2. Thus, we infer that r2 often has the same value across iterations.

To optimize this inefficiency, we introduce a conditional check on r2 such that the program can reuse the return value of function exp from the previous iteration if the value of r2 has not changed. This optimization eliminates 76% of the memory loads and 93% of the redundant memory loads, yielding a $1.39 \times$ speedup for the entire program.

VIII. THREATS TO VALIDITY

The threats mainly exist in applying LOADSPY for code optimization. The same optimization for one application may show different speedups on different computer architectures. A given load redundancy fraction may not help estimate the potential speedup. Some optimizations are input-specific, and a different profile may demand a different optimization. Based on the reported inefficiencies, programmers need to devise an optimization that is safe in any execution.

IX. CONCLUSIONS

In this paper, we presented a study of identifying program inefficiencies by focusing on whole-program load redundancy. We demonstrate that redundant load operations are often a symptom of various inefficiencies arising from inputs, suboptimal data structure and algorithm choices, and missed compiler optimizations. To pinpoint these inefficiencies in complex software code bases, we have developed LOADSPY, a fine-grained

```
1 for (k=0; k<(1+box[1].nn); k++) {
2    ...
3    for (i=0; i<NUMBER_PAR_PER_BOX; i=i+1) {
4        for (j=0; j<NUMBER_PAR_PER_BOX; j=j+1) {
5            r2 = rA[i].v + rB[j].v - DOT(rA[i],rB[j]);
6            u2 = a2*r2;
7            vij= exp(-u2);
8            fs = 2.*vij;
9            ...
10            }
11      }
12 }</pre>
```

Listing 19: Temporal load redundancy in Rodinia-3.1 lavaMD due to redundant function calls.

profiler that profiles load redundancy. LOADSPY toolchain provides valuable guidance to developers for code tuning—calling contexts of the two parties involved in a redundancy, narrowed-down redundancy scopes to focus on optimization, metrics to understand relative significance of redundancy, and a GUI for the source code attribution. We evaluate LOADSPY using several benchmarks and real-world applications. Guided by LOADSPY we are able to optimize prior-known and new inefficiencies in several programs. Eliminating temporal and spatial load redundancies resulted in nontrivial speedups.

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