Abstract—Extensive prior research has focused on alleviating the characteristic poor cache locality of graph analytics workloads. However, graph pre-processing tasks remain relatively unexplored. In many important scenarios, graph pre-processing tasks can be as expensive as the downstream graph analytics kernel. We observe that Propagation Blocking (PB), a software optimization designed for SpMV kernels, generalizes to many graph analytics kernels as well as common pre-processing tasks. In this work, we identify the lingering inefficiencies of a PB execution on conventional multicores and propose architecture support to eliminate PB’s bottlenecks, further improving the performance gains from PB. Our proposed architecture – COBRA – optimizes the PB execution of both graph processing and pre-processing alike to provide end-to-end speedups of up to 4.6x (3.5x on average).

1 Introduction

The increasing main memory capacities and core counts of modern processors has motivated a shift away from distributed graph processing towards analyzing graphs using just a single machine [1], [2], [3]. However, achieving high performance in single machine graph processing is challenging. Irregular memory accesses lead to poor cache locality and an execution time dominated by DRAM latency [4], [5]. Considerable focus has been directed towards improving the performance of graph analytics kernels using a variety of techniques including tiled executions, optimized data layouts, programming models, and custom architectures [4], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26].

Most prior works focus solely on optimizing the graph analytics kernel execution time, assuming an already pre-processed input graph stored in an optimized, sparse representation. Graph pre-processing tasks that build the sparse graph representations are assumed to be amortized over many executions and, hence, have received little attention. However, in scenarios such as processing time-evolving graphs [27], [28], [29] and one-shot processing [30], pre-processing times cannot be easily ignored [31].

In this work, we focus on the recently proposed Propagation Blocking (PB) optimization [32]. While PB was developed as a software-based cache locality optimization for PageRank, recent works have demonstrated PB’s effectiveness across a range of graph kernels [20], [33]. We observe that the key insight of PB – exploiting unordered parallelism to reorder irregular updates for improved cache locality – applies equally well to graph pre-processing. The broad applicability of PB across graph processing and pre-processing tasks makes PB an ideal candidate for acceleration with custom architecture support.

While PB is an effective locality optimization [32], all software-based PB executions suffer from two fundamental inefficiencies. First, we observe that PB performance is sensitive to a software parameter called bin range (the optimal value of which varies by application, input, and architecture). Second, to reorder irregular memory accesses, PB imposes non-trivial overheads in the form of executing many additional instructions.

We propose COBRA: a set of modifications to the ISA and the memory hierarchy of a multicore processor to eliminate the inefficiencies of a PB execution. Instead of executing additional instructions to reorder irregular updates as in software-based PB, COBRA introduces simple fixed-function logic in each level’s cache controllers to efficiently reorder irregular updates. COBRA introduces a single (CISC-like) instruction to offload the reordering computation to the fixed function units in each cache level. COBRA’s architecture extensions eliminate the instruction overhead of PB and also remove PB’s brittle dependence on the bin range parameter, instead defining PB parameters by architectural properties (size of each cache level). We evaluate COBRA across a common graph pre-processing task (converting an Edgelist representation of a graph into a CSR) and a common graph processing kernel (PageRank) and show that COBRA provides a mean speedup of 1.74x over an optimized software PB implementation. Furthermore, since COBRA applies to both graph processing and pre-processing, we show that COBRA is able to provide an end-to-end speedup of 3.5x on average.

2 Background

The goal of this work is to improve the performance of graph processing and pre-processing. To provide background, we characterize the cost of graph (pre)-processing and provide an overview of the Propagation Blocking (PB) optimization that applies to both graph processing and pre-processing.

Overview of Graph Processing: Graph analytics requires compressed representations because graphs are often extremely sparse (a typical adjacency matrix is ≥99% sparse [34]). Most frameworks [2], [7], [19] use the Compressed Sparse Row (CSR) format due to its memory efficiency and ability to quickly identify a vertex’s neighbors. Figure 1 shows a graph’s outgoing edges in CSR format. CSR uses two arrays to represent edges, sorting by edge source IDs. The Neighbor Array (NA) contiguously stores each vertex’s neighbors. The Offsets Array (OA) stores the starting offset of each vertex’s neighbor list in the NA. Directed graphs use CSR for storing outgoing neighbors, and Compressed Sparse Column (CSC) to store the transpose of the adjacency matrix, which represents incoming neighbors. Graph analytics kernels iteratively process vertices until meeting a convergence criterion. A graph kernel may iterate over a vertex’s outgoing neighbors (“push” execution) or incoming neighbors (“pull” execution) or dynamically switch between the two neighborhoods [2], [3]. Push-pull direction switching requires building both the CSC and CSR.
### The Cost of Graph Pre-processing

Most graph frameworks expect inputs in CSR/CSC format but graph repositories typically store graphs in the "coordinate list" COO format (also referred to as Edgelists) as shown in Figure 1. Therefore, converting the input graph to CSR/CSC is a necessary pre-processing step before any useful computation happens. The COO format is so prevalent that the Graph500 organization has assigned the computation of converting an Edgelist into a different representation as one of three kernels used to benchmark supercomputers for their graph processing capabilities [35].

#### Graph reordering

Graph reordering is another popular pre-processing step where structural properties of graphs (e.g. community structure [11], [20]) are exploited to change the labelling of vertex ids and create a new CSR with improved locality. Figure 2 shows the speedup of the Radii kernel running on graphs produced by a lightweight reordering technique (degree-sorting [10]). The data show that lightweight reordering is effective even after including the cost of constructing a new CSR. However, constructing the reordered CSR takes up 25%-55% of the total run time. The dominant computation in lightweight reordering and other sparse linear algebra pre-processing tasks such as constructing Compressed Sparse Fibers (CSF) for multi-dimensional tensors [36] are variations of Algorithm 1. Therefore, we focus on the Edgelist-to-CSR kernel as a representative computation for graph pre-processing.

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**Algorithm 1 Kernel to populate neighbors (Edgelist-to-CSR)**

| Line | Description |
|------|-------------|
| 1    | offsets ← PrefixSum(degrees) | Offsets Array (OA) |
| 2    | par_for e in EL do | Offset Array (OA) |
| 3    | neighbors[offsets[e.src]] ← e.dst | Neighbor Array (NA) |
| 4    | AtomicAdd(offsets[e.src], 1) |

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### Propagation Blocking (PB)

PB improves cache locality of applications dominated by irregular memory updates. We explain the intuition behind PB by applying it to the Edgelist-to-CSR kernel shown in Algorithm 1 (henceforth referred to as Neighbor-Populate). A baseline execution of Neighbor-Populate suffers from poor cache locality because edges may be arbitrarily ordered in the Edgelist, leading to fine-grain irregular accesses to the offsets array (Line 3; Algorithm 1). Accesses to the neighbors array are also irregular because they depend on the contents of the offsets array. A PB execution of the Neighbor-Populate kernel (shown in Algorithm 2) improves locality by breaking the execution into two phases – Binning and Bin-Read. During the Binning phase, neither offsets nor neighbors arrays are accessed. Instead, pairs of indices and update values (e.src, e.dst) are stored in one of several bins maintained by PB. A bin is a data structure that sequentially stores each update belonging to a particular range (the "bin range") of data elements. Once all updates have been written to bins, PB starts the second phase – Bin-Read. During Bin-Read, the tuples (index and update value pairs) in a bin are sequentially processed before moving to the next bin. Since each bin stores updates for a smaller index range, the range of random accesses to the offsets and neighbors arrays are reduced, allowing each bin's updates to fit in on-chip caches.

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**Algorithm 2 PB version of Algorithm 1**

1: offsets ← PrefixSum(degrees) | Binning Phase
2: par_for e in EL do | Bin-Read Phase
3: tid ← GetThreadID()
4: binID ← (e.src, BinRange)
5: bins[tid][binID] ← (e.src, e.dst)
6: par_for binID in NumBins |
7: for tid in NumThreads do |
8: for tuple in bins[tid][binID] do |
9: offsetVal ← offsets[tuple.src] |
10: neighbors[offsetVal] ← tuple.dst |
11: Add(offsets[tuple.src], 1)

Prior works [20], [33] have proposed optimizations to PB for applications with commutative updates. Commutativity allows coalescing multiple updates destined to the same index, reducing the number of tuples to be written to bins which reduces total memory traffic. We find that commutativity is not necessary to benefit from PB. The Neighbor-Populate kernel is an example of a non-commutative kernel. The updates to the offsets array in Neighbor-Populate (Line 4; Algorithm 1) are not commutative because the order of updates to the offsets array determines the contents of the neighbors array (NA). Coalescing updates to the offsets array (as proposed in prior PB optimizations [20], [33]) would break correctness by skipping elements of the NA. However, PB on its own is still applicable to Neighbor-Populate because the kernel allows a vertex’s neighbors to be listed in any order; the non-commutative updates permit unordered parallelism. Therefore, the applicability of PB goes beyond just commutative updates (Table 1).

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**Table 1:** Speedups from PB: PB is an effective optimization for both pre-processing and processing kernels across diverse input graphs

| Application | DBP | KRON | URND | EURO | HBUBL |
|-------------|-----|------|------|------|-------|
| NeighPop (Pre-processing) Speedup | 6.9x | 6.6x | 4.5x | 6.3x | 7.3x |
| PageRank (Pre-processing) Speedup | 1.3x | 1.1x | 1.2x | 0.8x | 1.2x |

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### 3 Opportunities for Improving PB

We identify the opportunities for optimizing PB without relying on update commutativity. In this section, we characterize the
two inefficiencies that all PB executions on conventional multi-core processors suffer from: (i) PB must compromise by selecting a sub-optimal bin range parameter, and (ii) binning updates in PB requires executing many additional instructions.

Compromising on the Bin Range: The bin range parameter in PB defines the range of indices mapped into a bin, and, indirectly, the number of bins \( \text{Bins} = \frac{\text{Unique Indices}}{\text{Bin Range}} \). To amortize the cost of writing to bins, the Binning phase uses cacheline-sized coalescing buffers (henceforth referred to as C-Buffers) for each bin that accumulate updates to bins and enable coarse granularity writes to bins. Consequently, the performance of both Binning and Bin-Read is sensitive to the bin range. Figure 3 shows performance counter results for Binning (left) and Bin-Read (right) as bin range varies, for the Neighbor-Populate kernel. The data show normalized L1 load misses (broken into L2, LLC, and DRAM accesses). Binning has the fewest cache misses with large bin ranges because all the bins’ C-Buffers fit in L1. In contrast, Bin-Read has the least cache misses with small bin range because the range of indices modified by a bin’s updates fits in the L1 cache (Lines 9-11; Algorithm 2). Competing requirements on the bin range by the two phases forces all PB executions to make a compromise, leading to sub-optimal performance in both phases (Table 2).

Overheads of binning in software PB: The second major source of inefficiency in PB is the need to execute additional instructions for binning updates and managing transfer of data between C-Buffers and bins in memory (Lines 4-5; Algorithm 2). Executing additional instructions degrades instruction level parallelism by stressing core resources (e.g., reservation stations, ROB, load-store queue). Through simulation studies, we found that PB executes up to 5x more instructions compared to a baseline execution of Neighbor-Populate and causes the branch misprediction rate to increase from \( \sim 0\% \) to \( \sim 10\% \).

Our characterization of PB reveals two opportunities for improving PB performance. First, an efficient PB execution must be able to avoid the compromise on the bin range parameter (i.e. simultaneously achieve optimal Binning and Bin-Read performance). Second, an efficient PB execution must avoid the extra instruction overhead for binning.

4 COBRA: An Architecture for Efficient PB

We present a new system called COBRA that specializes the cache hierarchy to eliminate the two inefficiencies of PB executions. COBRA’s architecture extensions are specifically targeted at improving Binning performance at small bin ranges. Since Bin-Read is naturally efficient at small bin ranges (Figure 3), the improved Binning performance allows COBRA to achieve performance close to ideal PB (Table 2).

Problem of Binning with small bin ranges: Binning has poor cache locality at small bin ranges. Figure 4 (left part) explains why Binning in PB performs poorly in a typical 3-level cache hierarchy. At small bin ranges, the number of bins is high and all the C-Buffers do not fit in a small (e.g., L1) cache, increasing the average latency of inserting tuples into C-Buffers. Compounding the problem, increased cache demands by other program data displaces C-Buffers to lower levels of cache (e.g., LLC) which further increases C-Buffer access latency.

Architecture support for Binning: The key insight of COBRA is to decouple Binning performance from the number of bins in memory. Instead of a single bin range that spreads C-Buffers across the cache hierarchy, COBRA maintains a hierarchy of C-Buffers. Each level of the cache hierarchy has a set of C-Buffers with a unique bin range that is specific to that level and maps tuples into that level’s C-Buffers. The number of C-Buffers in a cache level is bounded by the capacity of that level. The L1 cache has the fewest C-Buffers (largest bin range) and the Last Level Cache (LLC) has the most C-Buffers (smallest bin range). For example, in Figure 4, the L1, L2, and LLC have \( Y_1 \), \( Y_2 \), and \( Y_3 \) C-Buffers with bin ranges \( 16R \), \( 8R \), and \( R \) respectively.

COBRA introduces a new instruction called \texttt{binUpdate} whose operands are the index and update value that need to be binned. The \texttt{binUpdate} instruction interacts only with the L1 cache, writing tuples into one of the \( Y_1 \) C-Buffers identified by the L1BinRange \( (L1Buffer = \text{Index}, \text{L1BinRange}) \). When an L1 C-Buffer fills up with tuples, COBRA does not transfer its contents directly to an in-memory bin (as in baseline PB). Instead, COBRA executes the L1 C-Buffer by unpartitioning its tuples and sending each tuple to its C-Buffer in the L2 cache. Unlike a traditional cache eviction where the evicted line is sent to the next cache level as a whole, during a C-Buffer eviction each tuple in the filled C-Buffer may need to be written to a different C-Buffer in the next cache level. COBRA writes each tuple evicted from the L1 C-Buffer into one of the \( Y_2 \) C-Buffers in the L2 cache identified by the L2BinRange \( (L2Buffer = \text{Index}, \text{L2BinRange}) \). Similarly, when an L2 C-Buffer fills up, COBRA evicts it from L2 and sends each of its tuples to one of the \( Y_3 \) C-Buffers present in the LLC. Finally, when a LLC...
C-Buffer fills, COBRA transfers all the tuples in the filled LLC C-Buffer to the corresponding bin in main memory (as in baseline PB). In COBRA, each C-Buffer eviction results in scattering tuples across the C-Buffers of the next cache level. All tuples are first inserted into one of the L1 C-Buffers, then through evictions reach one of the LLC C-Buffers, and finally (on LLC C-Buffer eviction) are written into one of \( Y_3 \) bins in memory.

The binning process in COBRA is made efficient through two architecture extensions. First, COBRA relies on fixed-function units called binning engines in each cache level’s controllers to handle C-Buffer evictions (including unpacking tuples from a filled \( L_i \) C-Buffer and appending each tuple to an appropriate \( L_{i+1} \) C-Buffers). COBRA uses simple way-based cache partitioning (as shown in Figure 4) to pin C-Buffers to cache for the entirety of Binning, allowing simple logic to determine the unique location of a C-Buffer within a cache level. The binning engines allow COBRA to offload C-Buffer management to hardware, eliminating the instruction overhead of binning in PB. Second, COBRA uses a small number of eviction buffers between cache levels to hide the latency of scattering tuples during C-Buffer evictions. Removing the latency of C-Buffer evictions off the critical path is crucial in allowing COBRA to achieve ideal PB performance. For the example in Figure 4, the core sees a bin-update latency equivalent to binning into a small number of bins (\( Y_1 \)) associated with a large bin range (18-8) while actually operating on large number of bins (\( Y_3 \)) associated with a small bin range (8).

5 EXPERIMENTAL METHODOLOGY

We characterized graph pre-processing costs (Figure 2) and PB’s sensitivity to bin range (Figure 3) on a real-system (an Intel Xeon processor with 14 cores and 35MB LLC). For all other experiments, including evaluating COBRA’s performance, we use the Sniper [38] simulator to model an architecture with 16 Out-of-Order (OoO) cores, a three-level cache hierarchy with 2MB/core NUCA LLC, and mesh interconnect. We made various extensions to Sniper to model COBRA—adding support for non-temporal stores and ensuring that bin-update retires only when it reaches the head of the ROB because bin-update writes data caches (like stores). We use baseline implementations of Neighbor-Populate and Pagerank from the GAP benchmark [3]. We evaluate each workload across large input graphs [34] that are diverse in terms of degree-distribution (normal, power-law, bounded-degree), number of vertices (18-51 million), and average degrees (2-8). All the input graphs far exceed the LLC capacity. Finally, for the PB runs, we use the original PB source code which we received from the authors [32].

6 EVALUATION

COBRA improves the performance of PB substantially. The main result of this evaluation is that COBRA is effective across both graph processing and pre-processing. We study the reduction in total execution time of the graph analytics pipeline in Figure 4, building a CSR out of an Edgelist and running a graph analytics kernel on the CSR. Figure 5 shows the speedups of running Pagerank on an input graph initially stored as an Edgelist. The data show that even after including the pre-processing cost of constructing a CSR, running Pagerank on a CSR yields a mean speedup of 1.48x over running Pagerank directly on an Edgelist. Applying PB to both pre-processing and graph processing steps provides additional benefit, increasing the mean speedup over Edgelist-based Pagerank to 2.25x. Finally, COBRA optimizes both PB executions and increases the mean end-to-end speedup over Edgelist-based Pagerank to 3.5x.

Fig. 5: End to end speedups with COBRA: COBRA applies to both graph pre-processing (EL-to-CSR) and processing (PageRank)

COBRA improves PB performance in two ways – eliminating the compromise in bin range (achieving optimal Binning and Bin-Read performance) and eliminating the instruction overheads associated with binning. To isolate the contributions from each optimization, we compared the speedups from PB, PB-ideal (an idealized PB execution combining Binning at a large bin range with Bin-Read at a small bin range), and COBRA. Figure 6 shows that eliminating the compromise in bin range allows PB-ideal to achieve a mean speedup of 1.28x over PB. As discussed in Section 4, COBRA achieves close to PB-ideal performance by improving Binning performance at small bin ranges. Additionally, COBRA reduces the instruction overheads of binning in PB by offloading C-Buffer management to fixed-function binning engines in cache controllers. By reducing the instruction overheads associated with binning, COBRA is able to provide an additional speedup of 1.35x over PB-ideal. Combining the benefits from eliminating the compromise on bin range and avoiding instruction overheads of binning allows COBRA to provide a mean speedup of 1.74x over PB.

7 RELATED WORK

Milk [33] is a compiler-based approach that simplifies writing PB versions of applications. COBRA could potentially be a backend for the Milk compiler. GraBoost [39] exploits commutativity in PB for out-of-core graph analytics while COBRA targets in-memory analytics. PHI [20] is hardware-based PB optimization that uses simple ALUs at each cache level to support in-place coalescing of updates. Unfortunately, PHI relies on updates being commutative and is inapplicable to applications like Neighbor-Populate. In contrast, COBRA is applicable for non-commutative kernels and is a more general optimization for PB. For commutative updates, we note that COBRA could also employ simple ALUs within caches as proposed in PHI and we are working towards incorporating PHI’s update coalescing optimization into COBRA. Prior work [37, 40] also highlighted PB’s sensitivity to bin range. COBRA eliminates the need to tune the bin range by using a unique bin range for each cache level.

8 CONCLUSION

We proposed COBRA, a set of ISA extensions and cache hierarchy modifications, to accelerate PB performance. By eliminating the fundamental overheads of PB executions, COBRA achieves speedups of up to 2.3x over PB. As part of future work, we plan to investigate specializations for COBRA based on application properties (e.g. commutativity) and expand COBRA to other irregular application domains beyond graph analytics.
