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GraphMP: An Efficient Semi-External-Memory Big Graph Processing System on a Single Machine

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***Abstract*—Recent studies showed that single-machine graph processing systems can be as highly competitive as cluster-based approaches on large-scale problems. While several out-of-core graph processing systems and computation models have been proposed, the high disk I/O overhead could significantly reduce performance in many practical cases. In this paper, we propose GraphMP to tackle big graph analytics on a single machine. GraphMP achieves low disk I/O overhead with three techniques. First, we design a vertex-centric sliding window (VSW) computation model to avoid reading and writing vertices on disk. Second, we propose a selective scheduling method to skip loading and processing unnecessary edge shards on disk. Third, we use a compressed edge cache mechanism to fully utilize the available memory of a machine to reduce the amount of disk accesses for edges. Extensive evaluations have shown that GraphMP could outperform state-of-the-art systems such as GraphChi, X-Stream and GridGraph by 31.6x, 54.5x and 23.1x respectively, when running popular graph applications on a billion-vertex graph.**

***Index Terms*—Graph Processing, Big Data, Parallel Computing**

I. Introduction

In the era of “Big Data”, many real-world problems, such as social network analytics and collaborative recommendation, can be represented as graph computing problems [1]. Analyzing large-scale graphs has attracted considerable interest in both academia and industry. However, researchers are facing significant challenges in processing big graphs[1] with popular big data tools like Hadoop [2] and Spark [3], since these general-purpose frameworks cannot leverage inherent interdependencies within graph data and common patterns of iterative graph algorithms for performance optimization [4].

To tackle this challenge, many in-memory graph processing systems have been proposed over multi-core, heterogeneous and distributed infrastructures. These systems adopt a vertex-centric programming model (which allows users to think like a vertex when designing parallel graph applications), and should always manage the entire input graph and all intermediate data in memory. More specifically, Ligra [5], Galois [6], GraphMat [7] and Polymer [8] could handle generic graphs with 1-4 billion edges on a single multi-core machine. Several systems, e.g., [9], [10], [11], [12], [13], can scale up the processing performance with heterogeneous devices like GPU and Xeon Phi. To handle big graphs, Pregel-like systems, e.g., [14] [15], [16], [17], scale out in-memory graph processing to a cluster: they assign the input graph's vertices to multiple machines, and provide interaction between them using message passing along out-edges. PowerGraph [18] and PowerLyra [19] adopt a GAS (Gather-Apply-Scatter) model to improve load balance when processing power-law graphs: they split a vertex into multiple replicas, and parallelize the computation for it using different machines. However, current in-memory graph processing systems require a costly investment in powerful computing infrastructure to handle big graphs. For example, GraphX needs more than 16TB memory to handle a 10-billion-edge graph [20], [21].

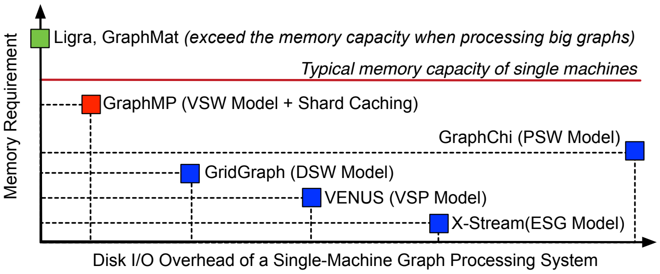


Fig. 1: GraphMP is a single-machine semi-external-memory graph processing system. Compared to in-memory systems like Ligra and GraphMat, GraphMP can handle big graphs on a single machine, since it does not store all graph data in memory. Compared to out-of-core systems (e.g., GraphChi, X-Stream, VENUS and GridGraph), GraphMP could fully utilize available memory of a typical server to reduce disk I/O overhead.

Out-of-core systems provide cost-effective solutions for big graph analytics. Single-machine approaches, such as GraphChi [22], X-Stream [23], VENUS [24] and GridGraph [25], breaks a graph into a set of small shards, each of which contains all required information to update a number of vertices. During the iterative computation, one iteration executes all shards. An out-of-core graph processing system usually uses three steps to execute a shard:

- loading its associated vertices from disk into memory;
- reading its edges from disk for updating vertices; and
- writing the latest updates to disk.

Therefore, there will be a huge amount of costly disk accesses, which can be the performance bottleneck [4]. To exploit the sequential bandwidth of a disk and reduce the amount of disk accesses, many computation models have been proposed, such as the parallel sliding window model (PSW) of GraphChi, the edge-centric scatter-gather (ESG) model of X-Stream, the vertex-centric streamlined processing (VSP) model of VENUS

[1] A big graph usually contains billions of vertices and hundreds of billions of edges.

TABLE I: Current approaches in graph processing engines, including their intended scale and performance.

	Single Machine (Multi-Core)			Single Machine (GPU/Xeon Phi)		Cluster	
Data Storage	**In-Memory**	**Out-of-Core**	**Semi-External-Memory**	**In-Memory**	**Out-of-Core**	**In-Memory**	**Out-of-Core**
Approaches	[5], [6] [7], [8]	[22], [23] [24], [25]	GraphMP (Our Approach)	[9], [10], [11] [12], [13]	[26], [27] (Use SSD)	[14], [15], [16] [17] [18], [19]	[28], [29]
Graph Scale (#edges)	1-4 Billion	5-200 Billion	5-200 Billion	1-4 Billion	>1 Trillion	5-1000 Billion	>1 Trillion
Performance (#edges/s)	1-2 Billion	5-100 Million	0.5-1.5 Billion	1-7 Billion	1-3 Billion	1-7 Billion	5-200 Million
Infrastructure Cost	Medium	Low	Medium	High	Medium	High	Medium

and the dual sliding windows (DSW) model of GridGraph. However, current out-of-core systems still have much lower performance (5-100M edges/s) than in-memory approaches (1-2B edges/s), as shown in Table I. While Chaos [29] and GraphD [28] scale out-of-core graph processing to multiple machines, their processing performance could not be significantly improved due to the high disk I/O overhead.

In this work, we propose GraphMP, a semi-external-memory (SEM) graph processing system, to tackle big graph analytics on a single commodity machine with low disk I/O overhead. GraphMP is design based on our previous work GraphH [30], which is a lightweight distributed graph processing framework. The concept of SEM arose as a functional computing approach for graphs, in which all vertices of a graph are managed in the main memory and the edges accessed from disk [31]. Several graph algorithms have been proposed to run in SEM, such as graph clustering and graph partitioning [31], [32]. Compared to these application-specific algorithms, GraphMP provides general-purpose vertex-centric APIs for common users to design and implement any parallel graph applications with performance guarantees. As shown in Figure 1, GraphMP can be distinguished from other single-machine graph processing systems as follows:

- Compared to in-memory approaches, GraphMP does not need to store all edges[2] in memory, so that it can handle big graphs on a single machine with limited memory.
- Compared to out-of-core approaches, GraphMP requires more memory to store all vertices. Most of the time, this is not a problem as a single commodity server can easily fit all vertices of a big graph into memory. Take PageRank as an example, a graph with 1.1 billion vertices needs 21GB memory to store all rank values and intermediate results. Meanwhile, a single EC2 M4 instance can have up to 256GB memory.
- Mosaic [26] and GTS [27] use heterogeneous computation devices (e.g., GPU and Xeon Phi) and PCIe/NVMe SSDs to support high performance big graph analytics on a single machine. In this paper, GraphMP is designed to run on a commodity multi-core server with HDDs.

GraphMP employs three main techniques. First, we design a **vertex-centric sliding window (VSW)** computation model. GraphMP breaks the input graph's vertices into disjoint intervals. Each interval is associated with a shard, which contains all edges that have destination vertex in that interval. During the computation, GraphMP slides a window on vertices, and processes edges shard by shard. When processing a specific shard, GraphMP first loads it into memory, then executes user-defined functions on it to update corresponding vertices. GraphMP does not need to read or write vertices on disk until the end of the program, since all of them are stored in memory. Second, we use Bloom filters to enable **selective scheduling**, so that inactive shards can be skipped to avoid unnecessary disk accesses and processing. Third, we leverage a **compressed shard cache mechanism** to fully utilize available memory to cache a partition of shards in memory. If a shard is cached, GraphMP would not access it from disk. GraphMP supports compressions of cached shards, and maximizes the number of cached shards with limited memory.

We implement GraphMP[3] using C++. Extensive evaluations on a testbed have shown that GraphMP performs much better than current single-machine out-of-core graph processing systems. When running popular graph applications, for example PageRank, single source shortest path (SSSP) and weakly connected components (WCC), on real-world large-scale graphs, GraphMP can outperform GraphChi, X-Stream and GridGraph by up to 31.6x, 54.5x, and 23.1x, respectively.

The rest of the paper is structured as follows. In section 2, we present the system design of GraphMP, including the VSW computation model, selective scheduling and compressed edge caching. Section 3 gives quantitative comparison between our approach with other single-machine graph processing systems. The evaluation results are detailed in Section 4. We conclude the paper in section 5.

II. System Design

In this section, we introduce the system design of GraphMP, including the vertex-centric sliding window (VSW) model, selective scheduling and compressed edge caching.

A. Notations

Given a graph $G = (V, E)$, it contains $|V|$ vertices and $|E|$ edges. Each vertex $v \in V$ has a unique ID $id(v)$, an incoming adjacency list $\Gamma_{in}(v)$, an outgoing adjacency list $\Gamma_{out}(v)$, a value $val(v)$ (which may be updated during the computation), and a boolean field $active(v)$ (which indicates whether $val(v)$ is updated in the last iteration). The in-degree and out-degree of v are denoted by $d_{in}(v)$ and $d_{out}(v)$. If vertex $u \in \Gamma_{in}(v)$, there is an edge $(u, v) \in E$. In this case, u is an incoming neighbor of v, and (u, v) is an in-edge of v. If $u \in \Gamma_{out}(v)$, u is an outgoing neighbor of v, and (v, u) is an out-edge of

[2] Real-world graphs usually contain much more edges than vertices [28].

[3] GraphMP is available at https://github.com/cap-ntu/GraphMP.

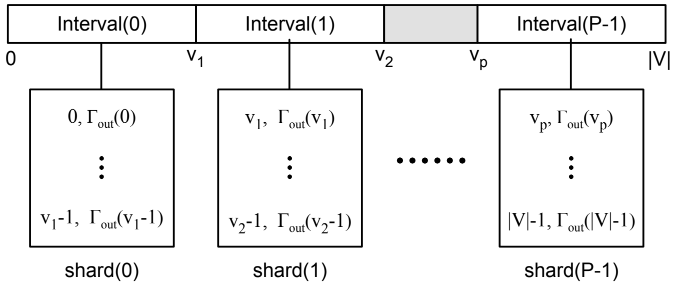


Fig. 2: The input graph's vertices are divided into P intervals. Each interval is associated with a shard, which stores all edges that have destination vertex in that interval. GraphMP structures all edges of a shard in key-value pairs $(id(v), \Gamma_{out}(v))$, and stores them in the Compressed Sparse Row format.

v. Let $val(u, v)$ denote the edge value of (v, u). In this paper, G is a unweighted graph, where $val(u, v) = 1, \forall(u, v) \in E$.

B. Graph Sharding and Data Storage

GraphMP partitions the input graph's edges into P shards. We use a similar graph sharing strategy like GraphChi [22]. As shown in Figure 2, the vertices of graph $G = (V, E)$ are divided into P disjoint intervals. Each interval is associated with a shard, which stores all the edges that have destination vertex in that interval. In GraphChi, all edges in each shard are ordered by their source vertex. As a comparison, GraphMP groups edges in a shard by their destination, and stores them in key-values pairs $(id(v), \Gamma_{in}(v))$. The number of shards, P, and vertex intervals are chosen with two policies: 1) any shard can be completely loaded into the main memory; 2) the number of edges in each shard is balanced. In this work, each shard approximately contains 18-22M edges, so that a single shard roughly needs 80MB memory. Users can select other vertex intervals during the preprocessing phase.

Each shard manages its assigned key-values pairs as a sparse matrix in the Compressed Sparse Row (CSR) format. One edge is treated as a non-zero entry of the sparse matrix. The CSR format of a shard contains a `row` array and a `col` array. The `col` array stores all edges' column indices in row-major order, and the `row` array records each vertex's adjacency list distribution. Each shard also stores the endpoints of its vertex interval. For example, given a shard, the incoming adjacency list of vertex v ($v_1 \leq v < v_2$) can be accessed from:

$$\Gamma_{in}(v) = \{col[row[v - v_1]], \cdots, col[row[v - v_1] - 1]\}.$$

Since all input graphs are unweighted in this paper, we do not need additional space to store edge values in the CSR format.

In addition to edge shards, GraphMP creates two metadata files. First, a property file contains the global information of the represented graph, including the number of vertices, edges and shards, and the vertex intervals. Second, a vertex information file stores several arrays to record the information of all vertices. It contains an array to record all vertex values (which can be the initial or updated values), an in-degree array and an out-degree array to store each vertex's in-degree and out-degree, respectively.

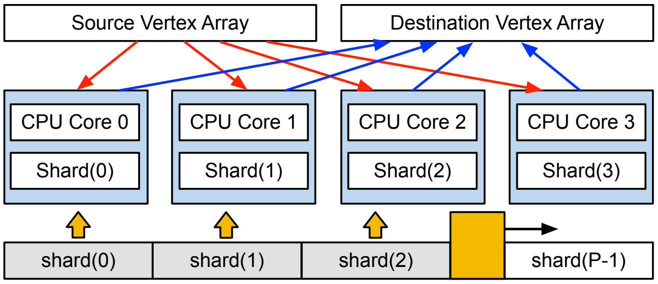


Fig. 3: The VSW computation model. GraphMP slides a window on vertices, and makes each CPU core process a shard at a time. When processing a shard, a CPU core continually pulls required vertex values from memory, and pushes updated ones to another array in memory.

Algorithm 1: Vertex-Centric Sliding Window Model

```
init (src_vertex_array, dst_vertex_array)
while active_vertex_ratio $> 0$ do
    # pragma omp parallel for num_threads(N)
    for shard $\in$ all_shards do
        if active_vertex_ratio $> 1/1000$ or
          Bloom_filter[shard.id].has(active_vertices) then
            load_to_memory(shard)
            for v $\in$ shard.associated_vertices do
                dst_vertex_array[v.id] $\leftarrow$ update(v,
                  src_vertex_array)
    active_vertices = {vertices that update their value}
    src_vertex_array $\leftarrow$ dst_vertex_array
    active_vertex_ratio $\leftarrow$ |active_vertices| / vertex_num
```

GraphMP uses following four steps to preprocess an input graph, and generates all edge shards and metadata files.

1) Scan the whole graph to get its basic information, and record the in-degree and out-degree of each vertex.
2) Compute vertex intervals to guarantee that, (1) each shard is small enough to be loaded into memory, (2) the number of edges in each shard is balanced.
3) Read the graph data sequentially, and append each edge to a shard file based on its destination and vertex intervals.
4) Transform all shard files to the CSR format, and persist the metadata files on disk.

After the preprocessing phase, GraphMP is ready to do vertex-centric computation based on the VSW model.

C. The Vertex-Centric Sliding Window Computation Model

*1) **Overview**:* GraphMP slides a window on vertices, and processes edges shard by shard on a single server with N CPU cores, as shown in Figure 3 and Algorithm 1. During the computation, GraphMP maintains two vertex arrays in memory until the end of the program: `SrcVertexArray` and `DstVertexArray`. The `SrcVertexArray` stores latest vertex values, which are the input of the current iteration. Updated vertex values are written into the `DstVertexArray`, which are used as the input of the next iteration. GraphMP uses

Algorithm 2: PageRank SSSP and WCC in GraphMP

```
1  Function PR_Update(Vertex v, Array src_vertex_array)
2      for e ∈ v.incoming_neighbours do
3          s += src_vertex_array[e.source] / e.source.out_deg
4      updated_value = 0.15 / num_vertex + 0.85 * s
5      return updated_value, (updated_value == v.value)

6  Function SSSP_Update(Vertex v, Array src_vertex_array)
7      for e ∈ v.incoming_neighbours do
8          d = min (src_vertex_array[e.source] + (e,u).val, d)
9      updated_value = min (d, v.value)
10     return updated_value, (updated_value == v.value)

11 Function WCC_Update(Vertex v, Array src_vertex_array)
12     for e ∈ v.incoming_neighbours do
13         group = min (src_vertex_array[e.source], group)
14     updated_value = min (group, v.value)
15     return updated_value , (updated_value == v.value)
```

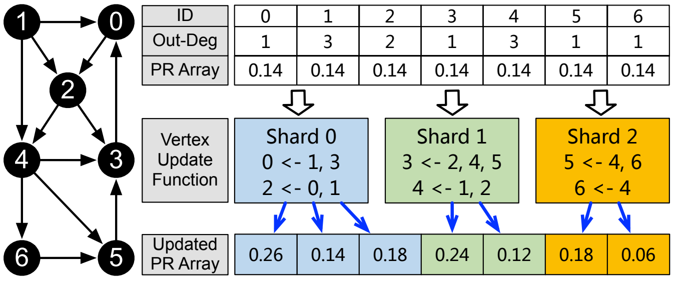
OpenMP to parallelize the computation (line 3 of Algorithm 1): each CPU core processes a shard at a time. When processing a specific shard, GraphMP first loads it into memory (line 6), then executes user-defined vertex-centric functions, and writes the results to the `DstVertexArray` (line 7-8). Given a vertex, if its values is updated, we call it an active vertex. Otherwise, it is inactive. After processing all shards, GraphMP records all active vertices in a list (line 9). This list could help GraphMP to avoid loading and processing inactive shards in the next iteration (line 5), which would not generate any updates (detailed in Section II-D). The values of `DstVertexArray` are used as the input of next iteration (line 10). The program terminates if it does not generate any active vertices (line 2).

*2) **Vertex-Centric Interface**:* Users only need to define an `Update` function for a particular application. The `Update` function accepts a vertex and `SrcVertexArray` as inputs,

```
Update(InputVertex, SrcVertexArray),
```

and should return two results: an updated vertex value which should be stored in `DstVertexArray`, and a boolean value to indicate whether the input vertex updates its value. Specifically, this function allows the input vertex to pull the values of its incoming neighbours from `SrcVertexArray` along the in-edges, and uses them to update its value.

We implement three graph applications, PageRank, SSSP and WCC, using the `Update` function in Algorithm 2. In PageRank, the input vertex accumulates all rank values along its in-edges (line 2-3), and uses it to its rank value accordingly (line 4). In SSSP, each input vertex tries to connect the source vertex (for example, vertex 0) along its in-edges (line 8), and finds the shortest path (line 9). In WCC, each vertex pulls the component ids of its neighbours (line 14), and selects the smallest one (including its current component id) as its newest component id (line 15).



ID	0	1	2	3	4	5	6
Out-Deg	1	3	2	1	3	1	1
PR Array	0.14	0.14	0.14	0.14	0.14	0.14	0.14
Updated PR Array	0.26	0.14	0.18	0.24	0.12	0.18	0.06

Fig. 4: This example illustrates the first iteration of PageRank on GraphMP.

*3) **Lock-Free Processing**:* GraphMP does not require any logical locks or atomic operations for graph processing using multiple CPU cores in parallel. This property could improve the processing performance considerably. As shown in Figure 3, GraphMP only uses one CPU core to process a shard for updating its associated vertices in each iteration. Given a vertex v, `DstVertexArray[v.id]`, is computed and written by a single CPU core. Therefore, there is no need to use logical locks or atomic operations to avoid data inconsistency issues on `DstVertexArray`. Many graph processing systems, such as GridGraph, use multiple threads to compute the updates for a single vertex in parallel. In this case, they should use costly logical locks or atomic operations to guarantee correctness.

*4) **Example**:* Figure 4 shows an example of how GraphMP run PageRank. The input graph is partitioned into three shards, each of which contains two vertices and their adjacency lists. At the beginning of PageRank, all vertex values are initiated to be $1/num\_vertex = 0.14$. GraphMP slides a window on vertices, and lets each CPU core process a shard at a time. When processing shard 0 on a CPU core, GraphMP pulls the values of vertex 1, 3 from `SrcVertexArray`, then use them to compute the updated value for vertex 0, and writes it to `DstVertexArray[0]`. After processing all 3 shards, GraphMP uses the values of `DstVertexArray` to replace the values of `SrcVertexArray`, and starts the next iteration if there are any active vertices.

D. System Optimizations

*1) **Selective Scheduling**:* For many graph applications, such as PageRank, SSSP and WCC, a lot of vertices converge quickly and would not update their values in the rest iterations. Given a shard, if all source vertices of its associated edges are inactive, it is an inactive shard. An inactive shard would not generate any updates in the following iteration. Therefore, it is unnecessary to load and process these inactive shards.

To solve the above problem, we use Bloom filters to detect inactive shards, so that GraphMP could avoid unnecessary disk accesses and processing. More specifically, for each shard, GraphMP manages a Bloom filter to record the source vertices of its edges. When processing a shard, GraphMP uses the corresponding Bloom filter to check whether it contains any active vertices. If yes, GraphMP would continue to load and

TABLE II: Analysis of graph computation models. C is the size of a vertex value, D is the size of one edge, $\delta \approx (1 - e^{-d_{avg}/P})P$, and $0 \leq \theta \leq 1$.

Category	PSW (GraphChi)	ESG (X-Stream)	VSP (VENUS)	DSW (GridGraph)	VSW (GraphMP)
Data Read	$C\|V\| + 2(C + D)\|E\|$	$C\|V\| + (C + D)\|E\|$	$C(1 + \delta)\|V\| + D\|E\|$	$C\sqrt{P}\|V\| + D\|E\|$	$\theta D\|E\|$
Data Write	$C\|V\| + 2(C + D)\|E\|$	$C\|V\| + C\|E\|$	$C\|V\|$	$C\sqrt{P}\|V\|$	0
Memory Usage	$(C\|V\|+2(C+D)\|E\|)/P$	$C\|V\|/P$	$C(2 + \delta)\|V\|/P$	$2C\|V\|/\sqrt{P}$	$2C\|V\| + ND\|E\|/P$

process the shard. Otherwise, GraphMP would skip it. For example, in Figure 4, when the sliding window is moved to shard 2, its Bloom filter could tell GraphMP whether vertex 4, 6 have changed their values in the last iteration. If there are no active vertices, the sliding window would skip shard 2, since it cannot not update vertex 5 or 6 after the processing.

GraphMP only enables selective scheduling when the ratio of active vertices is lower than a threshold. If the active vertex ratio is high, nearly all shards contain at least one active vertex. In this case, GraphMP wastes a lot of time on detecting inactive shards, and would not reduce any unnecessary disk accesses. As shown in Algorithm 1 Line 5, GraphMP starts to detect inactive shards when the active vertex ratio is low than a threshold. In this paper, we use 0.001 as the threshold. Users can choose a better value for specific applications.

*2) **Compressed Edge Caching**:* We design a cache system in GraphMP to reduce the amount of disk accesses for edges. The VSW computation model requires storing all vertices and edges under processing in the main memory. These data would not consume all available memory resources of a single machine. For example, given a server with 24 CPU cores and 128GB memory, when running PageRank on a graph with 1.1 billion vertices, GraphMP uses 21GB memory to store all data, including `SrcVertexArray`, `DstVertexArray`, the out-degree array, Bloom filters, and the shards under processing. It motivates us to build an in-application cache system to fully utilize available memory to reduce the disk I/O overhead. Specifically, when GraphMP needs to process a shard, it first searches the cache system. If there is a cache hit, GraphMP can process the shard without disk accesses. Otherwise, GraphMP loads the target shard from disk, and leaves it in the cache system if the cache system is not full.

To improve the amount of cached shards and further reduce disk I/O overhead, GraphMP can compress cached shards. In this work, we use two compressors (snappy and zlib), and four modes: mode-1 caches uncompressed shards; mode-2 caches snappy compressed shards; mode-3 caches zlib-1 compressed shards; mode-4 caches zlib-3 compressed shards. In zlib-N, N denotes the compression level of zlib. From mode-1 to mode-4, the cache system provides higher compression ratio (which can increase the amount of cached shards) at the cost of longer decompressing time. To minimize disk I/O overhead as well as decompression overhead, GraphMP should select the most suitable cache mode. More details on selecting the appropriate cache mode can be found in our previous work, GraphH [30].

III. Quantitative Comparison

We compare our proposed VSW model with four popular graph computation models: the parallel sliding window model (PSW) of GraphChi, the edge-centric scatter-gather (ESG) model of X-Stream, the vertex-centric streamlined processing (VSP) model of VENUS and the dual sliding windows (DSW) model of GridGraph. All systems partition the input graph into P shards or blocks, and run applications using N CPU cores. Let C denote the size of a vertex record, and D is the size of one edge record. For fair comparison and simplicity, we assume that the neighbors of a vertex are randomly chosen, and the average degree is $d_{avg} = |E|/|V|$. We disable selective scheduling, so that all system should process all edge shards or blocks in each iteration. We use the amount of data read and write on disk per iteration, and the memory usage as the evaluation criteria. Table II summarizes the analysis results.

A. The PSW Model of GraphChi

Unlike GraphMP where each vertex can access the values of its neighbours from `SrcVertexArray`, GraphChi accesses such values from the edges. Thus, the data size of each edge in GraphChi is $(C + D)$. For each iteration, GraphChi uses three steps to processes one shard: (1) loading its associated vertices, in-edges and out-edges from disk into memory; (2) updating the vertex values; and (3) writing the updated vertices (which are stored with edges) to disk. In step (1), GraphChi loads each vertex once (which incurs $C|V|$ data read), and accesses each edge twice (which incurs $2(C+D)|E|$ data read). In step (3), GraphChi writes each vertex into the disk (which incurs $C|V|$ data write), and writes each edge twice in two directions (which incurs $2(C + D)|E|$ data write). With the PSW model, the data read and write in total are both $C|V| + 2(C+D)|E|$. In step (2), GraphChi needs to keep $|V|/P$ vertices and their in-edges, out-edges in memory for computation. The memory usage is $(C|V| + 2(C + D)|E|)/P$.

B. The ESG Model of X-Stream

X-Stream divides one iteration into two phases. In phase (1), when processing a graph partition, X-Stream first loads its associated vertices into memory, and processes its out-edges in a streaming fashion: generating and propagating updates (the size of an update is C) to corresponding values on disk. In this phase, the size of data read is $C|V| + D|E|$, and the size of data write is $C|E|$. In phase (2), X-Stream processes all updates and uses them to update vertex values on disk. In this phase, the size of data read is $C|E|$, and the size of data write is $C|V|$. With the ESG model, the data read and write in total are $C|V| + (C + D)|E|$ and $C|V| + C|E|$, respectively. X-Stream only needs to keep the vertices of a partition in memory, so the memory usage is $C|V|/P$.

C. The VSP Model of VENUS

VENUS splits $|V|$ vertices into P disjoint intervals, each interval is associated with a g-shard (which stores all edges with destination vertex in that interval), and a v-shard (which contains all vertices appear in that g-shard). For each iteration, VENUS processes g-shards and v-shards sequentially in three steps: (1) loading a v-shard into the main memory, (2) processing its corresponding g-shard in a streaming fashion, (3) writing updated vertices to disk. In step (1), VENUS needs to process all edges once, which incurs $D|E|$ data read. In step (3), all updated vertices are written to disk, so the data write is $C|V|$. According to Theorem 2 in [33], each vertex interval contains $|V|/P$ vertices, and each v-shard contains up to $|V|/P + (1 - e^{-d_{avg}/P})|V|$ entries. Therefore, the data read and write are $C(1+\delta)|V| + D|E|$ and $C|V|$ respectively, where $\delta \approx (1 - e^{-d_{avg}/P})P$. VENUS needs to keep a v-shard and its updated vertices in memory, so the memory usage is $C(2 + \delta)|V|/P$.

D. The DSW Model of GridGraph

GridGraph group the input graph's $|E|$ edges into a "grid" representation. More specifically, the $|V|$ vertices are divided into $\sqrt{P}$ equalized vertex chunks and $|E|$ edges are partitioned into $\sqrt{P} \times \sqrt{P}$ blocks according to the source and destination vertices. Each edge is placed into a block using the following rule: the source vertex determines the row of the block, and the destination vertex determines the column of the block. GridGraph processes edges block by block. GridGraph uses 3 steps to process a block in the i-th row and j-th column: (1) loading the i-th source vertex chunk and the j-th destination vertex chunk into memory; (2) processing edges in a streaming fashion for updating the destination vertices; and (3) writing the destination vertex chunk to disk if it is not required by the next block. After processing a column of blocks, GridGraph reads $|E|/\sqrt{P}$ edges and $|V|$ vertices, and writes $|V|/\sqrt{P}$ vertices to disk. The data read and write are $C\sqrt{P}|V| + D|E|$ and $C\sqrt{P}|V|$, respectively. During the computation, GridGraph needs to keep two vertex chunks in memory, so the memory usage is $2C|V|/\sqrt{P}$.

E. The VSW Model of GraphMP

GraphMP keeps all source and destination vertices in the main memory during the vertex-centric computation. Therefore, GraphMP would not incur any disk write for vertices in each iteration until the end of the program. In each iteration, GraphMP should use N CPU cores to process P edge shards in parallel, which incurs $D|E|$ data read. Since GraphMP uses a compressed edge cache mechanism, the actual size of data read of GraphMP is $\theta D|E|$, where $0 \leq \theta \leq 1$ is the cache miss ratio. During the computation, GraphMP manages $|V|$ source vertices (which are the input of the current iteration) and $|V|$ destination vertices (which are the output the current iteration and the input of the next iteration) in memory, and each CPU core loads $|E|/P$ edges in memory. The total memory usage is $2C|V| + ND|E|/P$.

As shown in Table II, the VSW model of GraphMP could achieve lower disk I/O overhead than other computation models, at the cost of higher memory usage. In Section IV, we use experiments to show that a single commodity machine could provide sufficient memory for processing big graphs with the VSW model.

IV. Performance Evaluations

In this section, we evaluate GraphMP's performance using a physical server with three applications (PageRank, SSSP, WCC) and four datasets (Twitter, UK-2007, UK-2014 and EU-2015). The physical server contains two Intel Xeon E5-2620 CPUs, 128GB memory, 4x4TB HDDs (RAID5). Following table shows the basic information of used datasets. All datasets are real-word power-law graphs, and can be downloaded from http://law.di.unimi.it/datasets.php.

Dataset	Vertex Num	Edge Num	Avg Deg	Max Indeg	Max Outdeg	Size (CSV)
Twitter	42M	1.5B	35.3	0.7M	770K	25GB
UK-2007	134M	5.5B	41.2	6.3M	22.4K	93GB
UK-2014	788M	47.6B	60.4	8.6M	16.3K	0.9TB
EU-2015	1.1B	91.8B	85.7	20M	35.3K	1.7TB

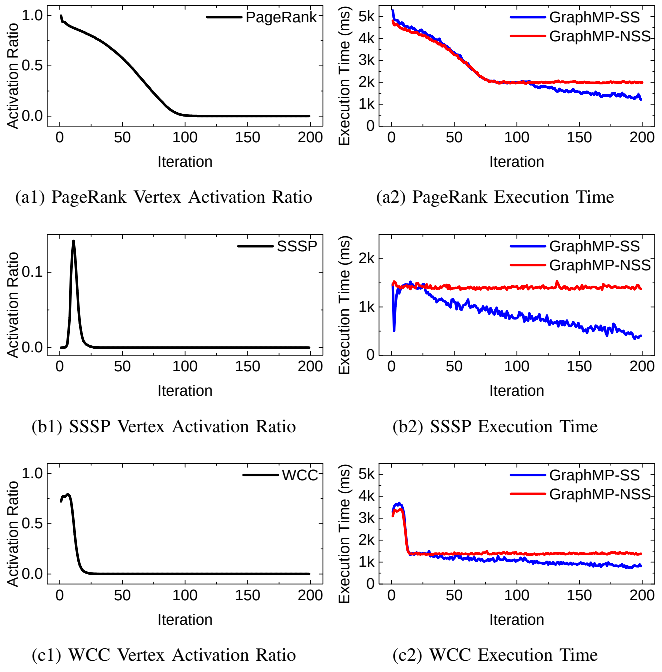
We first evaluate GraphMP's selective scheduling mechanism. Then, we compare the performance of GraphMP with an in-memory graph processing system, GraphMat. Next, we compare the performance of GraphMP with three out-of-core systems: GraphChi, X-Stream and GridGraph.

A. Effect of GraphMP's Selective Scheduling Mechanism

To see the effect of GraphMP's selective scheduling mechanism, we run PageRank, SSP and WCC on UK-2007 using GraphMP-SS and GraphMP-NSS, and compare their performance. Specifically, GraphMP-SS enables selective scheduling, so that it can use Bloom filters to detect and skip inactive shards. In GraphMP-NSS, we disable selective scheduling, so that it should process all shards in each iteration. Figure 5 shows that GraphMP's selective scheduling mechanism could improve the processing performance for all three applications.

As shown in Figure 5 (a1), many vertices converge quickly when running PageRank on UK-2007. Specifically, after the 110-th iteration, less than 0.1% of vertices update their values in an iteration (i.e., the vertex activation ratio is less than 0.1%). After that iteration, GraphMP-SS enables its selective scheduling mechanism, and it continually reduces the execution time of an iteration. In particular, GraphMP-SS only uses 1.2s to execute the 200-th iteration. As a comparison, GraphMP-NSS roughly uses 2s per iteration after the 110-th iteration. In this case, the selective scheduling mechanism could improve the processing performance of a single iteration by a factor of up to 1.67, and improve the overall performance of PageRank by 5.8%.

From Figure 5 (b1) and (b2), we can find that SSSP benefits a lot from GraphMP's selective scheduling mechanism. In this experiment, GraphMP updates more than 0.1% of vertices in a few iterations. Therefore, GraphMP-SS continuously reduce



(a1) PageRank Vertex Activation Ratio

(a2) PageRank Execution Time

(b1) SSSP Vertex Activation Ratio

(b2) SSSP Execution Time

(c1) WCC Vertex Activation Ratio

(c2) WCC Execution Time

Fig. 5: Effect of the selective scheduling mechanism. GraphMP-SS enables the selective scheduling mechanism. GraphMP-NSS disables the selective scheduling mechanism. We use UK-2007 as the input of all three experiments. The vertex activation ratio denotes the number of active vertices of an iteration.

the computation time from the 15-th iteration, and uses 0.4s in the 200-th iteration. As a comparison, GraphMP-NSS roughly uses 1.4s per iteration. In this case, GraphMP's selective scheduling mechanism could speed up the computation of an iteration by a factor of up to 2.86, and improve the overall performance of SSSP by 50.1%.

GraphMP's selective scheduling mechanism is enabled after the 31-th iteration of WCC, as shown in Figure 5 (c1) and (c2). GraphMP-SS begins to outperform GraphMP-NSS from that iteration. In particularly, GraphMP-SS uses 0.8s in the 200-th iteration, and GraphMP-SS uses 1.4. In this case, GraphMP's selective scheduling mechanism could reduce the computation time of an iteration by a factor of up to 1.75, and improve the overall performance of WCC by 9.5%.

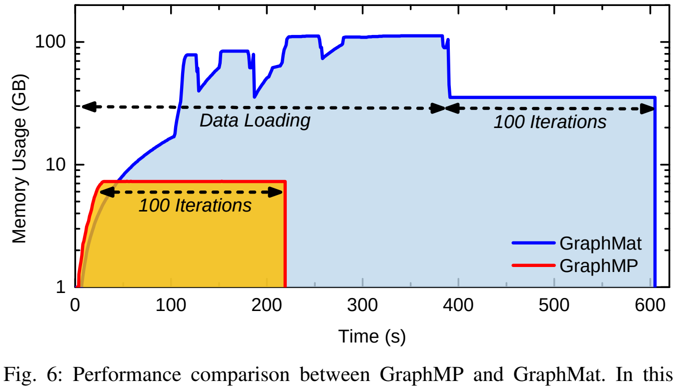
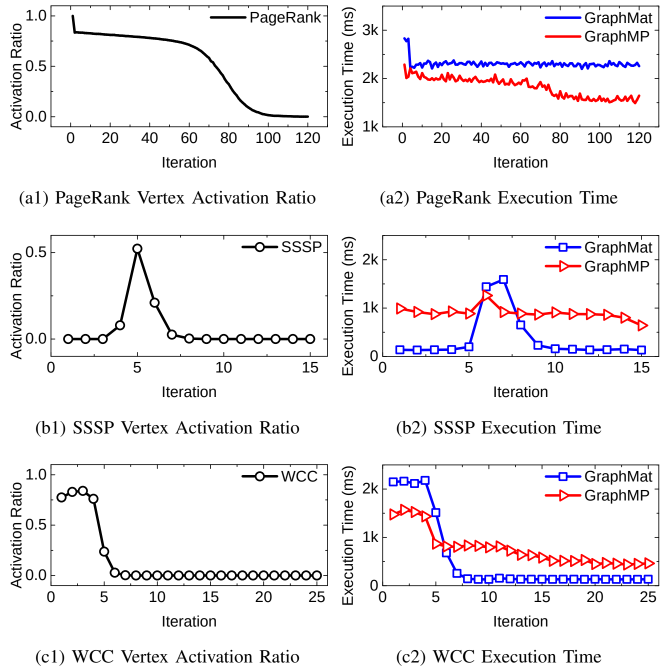


Fig. 6: Performance comparison between GraphMP and GraphMat. In this experiment, we run PageRank on the Twitter dataset.



(a1) PageRank Vertex Activation Ratio

(a2) PageRank Execution Time

(b1) SSSP Vertex Activation Ratio

(b2) SSSP Execution Time

(c1) WCC Vertex Activation Ratio

(c2) WCC Execution Time

Fig. 7: Performance comparison between GraphMP and GraphMat to run PageRank, SSSP and WCC on Twitter. We do not consider the data loading time in these experiments. The vertex activation ratio denotes the number of active vertices of an iteration.

B. GraphMP vs. GraphMat

We compare the performance of GraphMP with GraphMat, which is an in-memory graph processing system. GraphMat maps vertex-centric programs to sparse vector-matrix multiplication (SpMV) operations, and leverages sparse linear algebra techniques to improve the performance of graph computation.

GraphMat cannot handle big graph analytics in our testbed with 128GB memory. At the beginning of each application, GraphMat should load the entire graph into memory, and constructs required data structures. When running PageRank on the Twitter dataset, GraphMat uses up to 122GB memory for data loading, as shown in Figure 6. GraphMat cannot process UK-2007, UK-2014 and EU-2015 in our testbed, since the program can easily crash during the data loading phase caused by the out-of-memory (OOM) problem. Also, the data loading of GraphMat is costly: it uses 390s for data loading before running PageRank. As a comparison, GraphMP uses 7.3GB memory (including Bloom filters and compressed edge cache) to run PageRank on Twitter, and takes 30s for data loading. During the data loading phase, GraphMP scans all edges to construct Bloom filters, and places processed shards in the cache if possible. Compared to GraphMat, GraphMP could speed up PageRank on Twitter by a factor of 2.7 when considering both data loading and processing time.

Figure 7 shows the ratio of active vertices and the execution time per iteration when running PageRank, SSSP and WCC on the Twitter dataset with GraphMat and GraphMP. If we do not consider the data loading overhead, GraphMP can

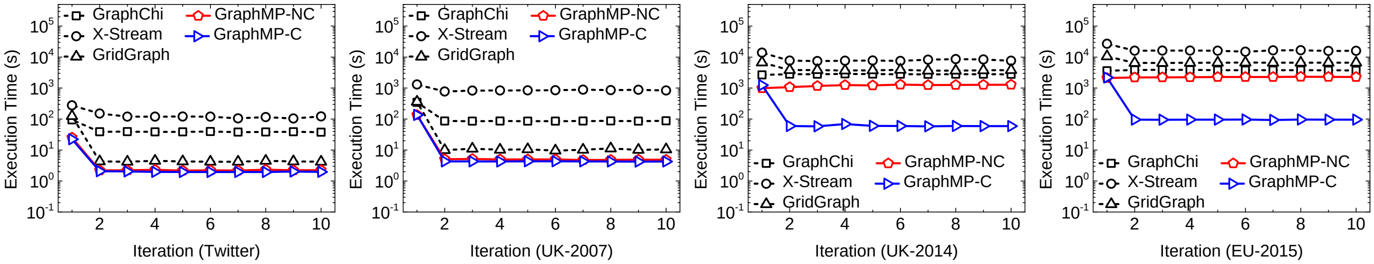


Fig. 8: The execution time of GraphChi, X-Stream, GridGraph and GraphMP to run PageRank on Twitter, UK-2007, UK-2014 and EU-2015.

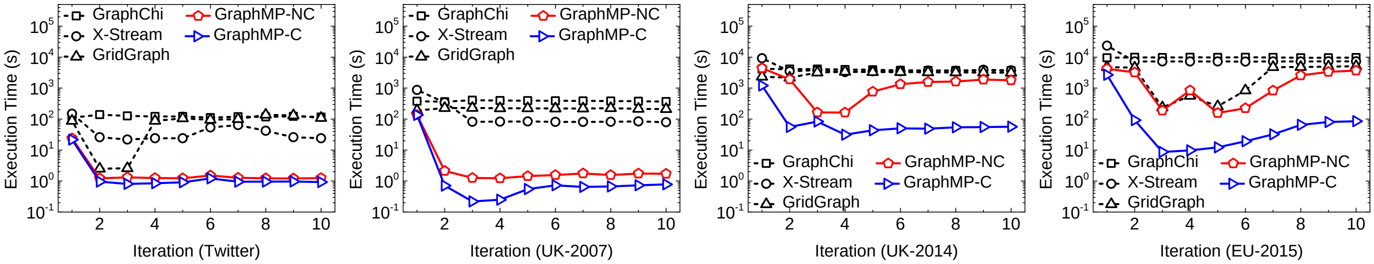


Fig. 9: The execution time of GraphChi, X-Stream, GridGraph and GraphMP to run SSSP on Twitter, UK-2007, UK-2014 and EU-2015.

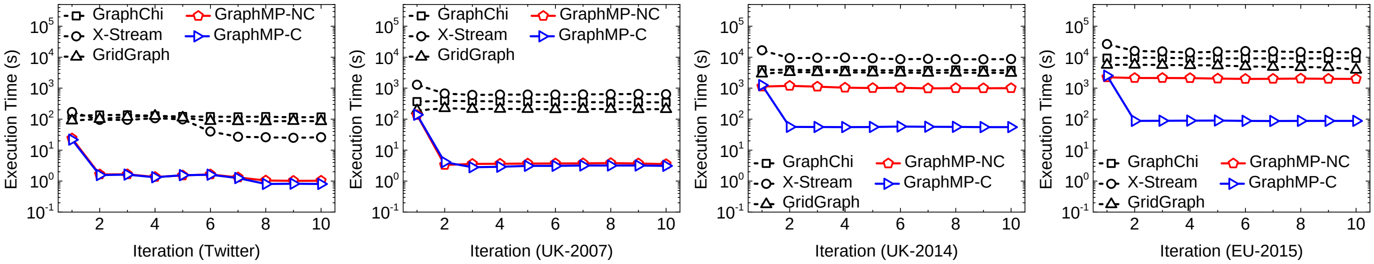


Fig. 10: The execution time of GraphChi, X-Stream, GridGraph and GraphMP to run WCC on Twitter, UK-2007, UK-2014 and EU-2015.

outperform GraphMat for PageRank, and GraphMat outperforms GraphMP for SSSP and WCC, since GraphMP employs many sparse linear algebra techniques to improve the performance of SpMV. Specifically, GraphMat takes 28s to run PageRank, and GraphMP uses 22s. For SSSP, GraphMat uses 1.3s, while GraphMP needs 9.9s. The corresponding values of WCC for GraphMat and GraphMP are 1.5s and 2.1s, respectively. However, running times without loading times are in seconds, which do not really matter. When considering the combined running time, GraphMP could provide much higher performance than GraphMat for all three applications.

C. GraphMP vs. GraphChi, X-Stream and GridGraph

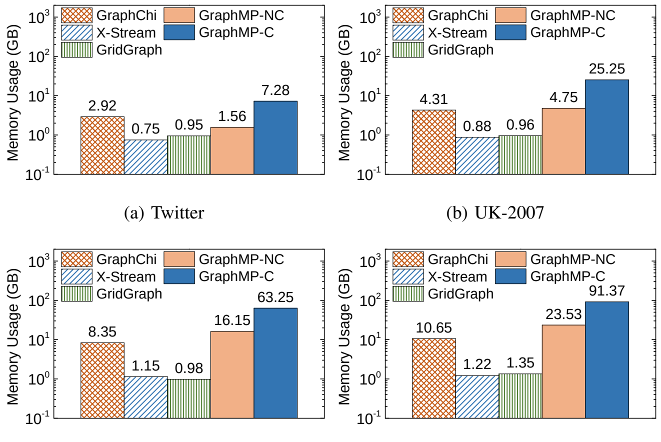
In this set of experiments, we compare the performance of GraphMP with three out-of-core graph processing systems: GraphChi, X-Stream and GridGraph. We do not use VENUS, since it is not open source. We run PageRank, SSSP and WCC on Twitter, UK-2007, UK-2014 and EU-2015, and record their processing time of 10 iterations and memory usage. To see the effect of GraphMP's compressed cache mechanism, we disable it in GraphMP-NC, enable it in GraphMP-C, and measure their performance separately. For fair comparison and simplicity, the first iteration's execution time of each application includes the data loading time.

TABLE III: Performance speedup ratios compared to GraphMP-C.

	Dataset	GraphChi	X-Stream	GridGraph	GraphMP-NC
PageRank	**Twitter**	11.0	33.8	4.1	1.1
	UK-2007	6.4	51.1	2.6	1.0
	UK-2014	15.7	47.6	22.8	6.8
	EU-2015	12.5	54.5	23.1	7.4
SSSP	**Twitter**	39.9	15.0	28.4	1.2
	UK-2007	27.4	13.3	15.5	1.1
	UK-2014	22.6	24.3	17.7	9.1
	EU-2015	31.6	28.8	10.0	6.3
WCC	**Twitter**	37.8	21.5	28.3	1.1
	UK-2007	21.7	41.6	12.6	1.0
	UK-2014	21.7	55.6	18.0	6.0
	EU-2015	28.0	48.8	15.5	6.2

Figure 8, 9 and 10 show the execution time of each iteration with different systems, datasets and applications. We could observe that GraphMP can considerably improve the graph processing performance, especially when dealing with big graphs. Table III shows the detail speedup ratios. The performance gain comes from three contributions: the VSW model, selective scheduling, and compressed edge caching.

When running PageRank on EU-2015, GraphMP-NC could



(a) Twitter

(b) UK-2007

(c) UK-2014

(d) EU-2015

Fig. 11: Memory usage of 5 graph processing systems to run PageRank on Twitter, UK-2007, UK-2014 and EU-2015. We disable the compressed cache mechanism in GraphMP-NC, and enable it in GraphMP-C.

outperform GraphChi, X-Steam and GridGraph by 1.7x, 7.3x and 3.1x, respectively. If we enable compressed edge caching, GraphMP-C further improves the processing performance by a factor of 7.4. GraphMP-C could outperform GraphChi, X-Steam and GridGraph by 12.5x, 54.5x and 23.1x to run PageRank on EU-2015, respectively.

When running SSSP, only a small part of vertices may update their values in an iteration. Thanks to the selective scheduling mechanism, GraphMP-NC and GraphMP-C could skip loading and processing inactive shards to reduce the disk I/O overhead and processing time. For example, when running SSSP on EU-2015 with GraphMP-NC and GraphMP-C, the third iteration uses less time than others, since a lot of shards are inactive. We observe that GridGraph also supports selective scheduling, since it has less computation time in an iteration with just a few of active vertices. When running SSSP on EU-2015, GraphMP-NC could outperform GraphChi, X-Steam and GridGraph by 5.0x, 4.6x and 1.6x, respectively. The GraphMP's compressed edge caching mechanism further reduces the processing time by a factor of 6.3. Thus, GraphMP-C could outperform GraphChi, X-Steam and GridGraph by 31.6x, 28.8x and 10.0x to run SSSP on EU-2015, respectively.

When running WCC on EU-2015, GraphMP-NC could outperform GraphChi, X-Steam and GridGraph by 4.5x, 7.8x and 2.5x, respectively. This performance gain is due to the VSW computation model with less disk I/O overhead. If we enable compressed edge caching, GraphMP-C could further improve the processing performance by a factor of 6.2. GraphMP-C can outperform GraphChi, X-Steam and GridGraph by 28.0x, 48.8x and 15.5x to run WCC on EU-2015, respectively.

In Figure 11, we show the memory usage of each graph processing system to run PageRank. We can see that GraphMP-NC uses more memory than GraphChi, X-Stream and GridGraph, since it keeps all source and destination vertices in memory during the computation. For example, when running PageRank on EU-2015, GraphChi, X-Stream and GridGraph only use 10.65GB, 1.22GB and 1.35GB memory, respectively. The corresponding value of GraphMP-NC is 23.53GB. GraphChi, X-Stream and GridGraph are designed and optimized for large-scale graph processing on a single common PC rather than a commodity server or a cloud instance. Even if our testbed has 128GB memory, these systems cannot efficiently use them. If we enable compressed edge cache, GraphMP-C uses 91.37GB memory to run PageRank on EU-2015. In this case, GraphMP-C roughly uses 68GB as cache. Thanks to the compression techniques and the compact data structure used in GraphMP, GraphMP-C can store all 91.8 billion edges in the cache system using 68GB memory. Thus, there are even no disk accesses for edges during the computation after the data loading phase. While GraphMP-C needs additional time for shard decompression, it can still considerably improve the processing performance due to the reduced disk I/O overhead.

V. Conclusion

In this paper, we tackle the challenge of big graph analytics on a single commodity server. Existing out-of-core approaches have poor processing performance due to the high disk I/O overhead. To solve this problem, we propose a SEM graph processing system named GraphMP, which maintains all vertices in the main memory during the computation. GraphMP partitions the input graph into shards, each of which contains a similar number of edges. Edges with the same destination vertex appear in the same shard. We use three techniques to improve the graph processing performance by reducing the disk I/O overhead. First, we design a vertex-centric sliding window (VSW) computation model to avoid reading and writing vertices on disk. Second, we propose selective scheduling to skip loading and processing unnecessary shards on disk. Third, we use compressed edge caching to fully utilize the available memory resources to reduce the amount of disk accesses for edges. With these three techniques, GraphMP could efficiently support big graph analytics on a single commodity machine. Extensive evaluations show that GraphH could outperform GraphChi, X-Stream and GridGraph by up to 31.6x, 54.5x, and 23.1x, respectively.

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