Trading Memory versus Workload Overhead in Graph Pattern Matching on Multiprocessor Systems

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Abstract: Graph pattern matching (GPM) is a core primitive in graph analysis with many applications. Efficient processing of GPM on modern NUMA systems poses several challenges, such as an intelligent storage of the graph itself or keeping track of vertex locality information. During query processing, intermediate results need to be communicated, but target partitions are not always directly identifiable, which requires all workers to scan for requested vertices. To optimize this performance bottleneck, we introduce a Bloom filter based workload reduction approach and discuss the benefits and drawbacks of different implementations. Furthermore, we show the trade-offs between invested memory and performance gain, compared to fully redundant storage.

1 INTRODUCTION

To satisfy the ever-growing computing power demand, hardware vendors improve their single hardware systems by providing an increasingly high degree of parallelism. In this direction, large-scale symmetric multiprocessor (SMP) are the next parallel hardware wave (Borkar et al., 2011). These SMP systems are characterized by each processor having the same architecture e.g. a multicore and all multiprocessors share a common memory space. This SMP type can be further classified into SMP with uniform memory access (UMA) and SMP with non-uniform memory access (NUMA), with the latter being the dominant approach. Both allow all processors to access the complete memory, but with different connectivity. This is a completely different hardware approach, since former processor generations got more performant by increasing their core frequency, leading to a higher performance at a free lunch. This effect came to an end due to power and thermal constraints. Thus, speedups will only be achieved by adding more parallel units. However, these have to be utilized in an appropriate way (Borkar et al., 2011; Sutter, 2005).

In addition to a very high number of cores, these large-scale NUMA-SMP systems also feature main memory capacities of several terabytes (Borkar et al., 2011; Kissinger et al., 2014). For applications like graph processing, this means that large graphs can be stored completely in memory and efficiently processed in parallel. Fundamentally, the meaning of graphs as data structure is increasing in a wide and heterogeneous spectrum of domains, ranging from recommendations in social media platforms to analyzing protein interactions in bioinformatics (Paradies and Voigt, 2017). Based on that, graph analytics is also increasingly attractive to acquire new insights from graph-shaped data. In this context, graph pattern matching (GPM) is an important, declarative, topology-based query mechanism and a core primitive. The pattern matching problem is to find all possible subgraphs within a graph that match a given pattern. The calculation of graph patterns can get prohibitively expensive due to the combinatorial nature. To efficiently compute graph patterns on such large-scale systems, we already proposed a NUMA-aware GPM infrastructure in (Krause et al., 2017a; Krause et al., 2017b), which is based on a *data-oriented architecture* (DORA) (Kissinger et al., 2014; Pandis et al., 2010). As Figure 1 shows, our infrastructure is characterized by implicitly partitioning graphs into small partitions and each partition is placed in the local memory of a specific NUMA node. Moreover, we use a *thread-to-data* mapping, such that each local hardware thread runs a worker. These are limited to operate exclusively on local graph partitions. Based on that, the calculation of pattern matching flows from

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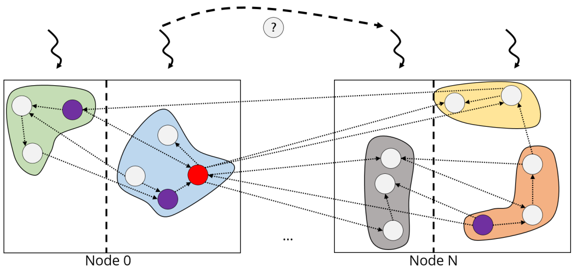


Figure 1: Data-oriented graph partitioning with thread assignment.

thread to thread depending on the data being accessed. Our previous work shows good scalability, whereby the graph partitioning has a high performance impact. This is remedied by a set of indicators, which we use to select the optimal partitioning strategy for a given graph and workload in (Krause et al., 2017a).

Our Contribution. DORA enables us to fully utilize all cores to efficiently process a pattern query in a highly parallel way. However, since we need to explicitly exchange intermediate results between workers, our whole approach depends on how we store the graph. If we only consider outgoing edges in a directed graph, we cannot always determine exactly to which partition (workers) the intermediate results have to be sent for further processing. In this case, we have to send them to all workers using a broadcast. This can be mitigated by also storing incoming edges as full redundancy. The consequence is doubled memory consumption, but we can send unicasts, because target vertices can be directly looked up. We propose to employ a Bloom filter based solution, which reduces broadcasts to a couple of unicasts, while only requiring a fraction of the memory overhead compared to full redundancy. Thus, our trade off for memory vs. workload overhead remains bearable.

Outline. This paper is structured as follows: In section 2, we briefly introduce our graph data model including an illustration of GPM. Then, we introduce our *Bloom filter*-based approach to efficiently trade memory versus workload overhead for GPM on large-scale NUMA-SMP systems in Section 3. Based on that, Section 4 describes selected evaluation results. Finally, we close the paper with related work and a short conclusion in Sections 5 and 6.

2 DATA MODEL AND PATTERN MATCHING

Within this paper, we focus on *edge-labeled multigraphs* (ELMGs) as a general and widely employed graph data model (Pandit et al., 2007; Otte and Rousseau, 2002). An ELMGs $G(V,E,\rho,\Sigma,\lambda)$ consists of a set of vertices V, a set of edges E, an incidence function $\rho : E \to V \times V$, and a labeling function $\lambda : E \to \Sigma$ that assigns a label to each edge. Hence, ELMGs allow any number of labeled edges between a pair of vertices, with RDF being a prominent example (Decker et al., 2000). This model does not impose any limitation, since e.g. property graphs can also be expressed as directed ELMGs through introducing additional vertices and edges for properties.

Storing a graph can be done manifold. One of the most intuitive and straightforward ways is to store all outgoing edges of a vertex as an edge list, which we call *outgoing edge storage (OES)*. This way, the topology of the graph can be represented precisely and lossless. To conform with DORA, we store all outgoing edges of one vertex within the same partition. Measures for balanced partitioning are necessary and applied, but out of scope of this work.

As mentioned in Section 1, *GPM* is a declarative topology-based querying mechanism. The query is given as a graph-shaped pattern and the result is a set of matching subgraphs (Tran et al., 2009). A well-studied mechanism for expressing such query patterns are *conjunctive queries (CQs)* (Wood, 2012), which decompose the pattern into a set of *edge predicates* each consisting of a pair of vertices and an edge label. Following this, the example query $(A) \to$ (RedVertex) $\to (B)$ is decomposed into the conjunctive query $\{(V_A) \to (V_{red}),\ (V_{red}) \to (V_B)\}$. Answering this query is easy using OES for Figure 1, since we only need to lookup all matches for V_A first and do the same for all found (V_{red}) subsequently. This is done by sending a single *unicast message* between two workers, communicating the intermediate results. This is straightforward, since the OES is partitioned by the *vertex ids*, which can be directly looked up to find their corresponding partition. Adding edge labels speeds up this process, as they increase the queries selectivity. However, reversing one of the edges, e.g. as in $(A) \to$ (RedVertex) $\leftarrow (B)$, the process gets complicated. The first step remains the same, but finding all vertices (V_B) now requires a *broadcast message* targeting all partitions. The OES does not allow direct lookup of target vertices, thus we need to activate all workers to scan their partitions, if there is a (V_B), which has (V_{red}) as target vertex. Hence, the workers processing the grey and yellow partition perform unnecessary work which should be avoided.

3 TRADING MEMORY VERSUS WORKLOAD OVERHEAD

Processing GPM on NUMA-SMP systems poses several challenges. With the data partitioning being a prominent example, another obstacle is the available vertex locality information, based on the edge storage. In our previous work (Krause et al., 2017b), we have shown the influence of incomplete vertex locality information, due to OES. We found, that answering queries with backward edges results in the activation of all workers (i.e. sending a broadcast), to find out, which partition actually contains the requested vertices.The resulting workload overhead can have significant performance impact and should thus be avoided; i.e. the reduction of messages in the system is highly desirable. A straightforward solution for this problem is to simply store full redundancy, i.e. reversing all edges and store them partitioned by the target vertex as incoming edges. This incoming edge storage (IES) adds a twofold storage overhead, but can increase the system performance dramatically. That is, since workers, which do not contain a requested vertex from a broadcast, do not get stalled with excess calls and can perform their actual work in time. However, when the stored graph grows or when there is a tighter memory budget, this approach is not feasible anymore. The consequence is to find a trade off between the invested memory for the gained performance. There is one direct fit for this requirement: *A Bloom filter*. The probabilistic data structure can be scaled in its size, which implicates varying accuracy and thus allows us to trade invested memory for workload.

Bloom Filter Design Aspects. Instead of storing each element completely and as-is, requiring large amounts of storage capacity, the Bloom filter refers to a few bits to remember a vertex' presence. Filling is performed by a hash function, which is applied to the vertex *id*, with the result denoting the slot number into a bitfield, denoting the bit to set to 1. To check whether a vertex *id* is present, its hash is calculated and the bitfield is checked, whether it contains a 1 or 0 at the index given by the hash. By not fully describing each vertex, this represents a probabilistic data structure with a false positive rate, i.e. returning *true*, even if a vertex is not present. Yset, false negatives, i.e. returning a *false* for a vertex which is actually present, are forbidden. Due to collisions, using just one bit per vertex, usually yields false positive rates above an acceptable level. Hence implementations use more than one hash per element, where $H_i'(x) \overset{!}{\neq} H_j'(x)\ \forall x$ and $i \neq j$. For each hash, a 1 is stored within the corresponding bit. When querying, the element *might* exist, if *all* bitfield indices contain a 1. The false positive rate p thus depends on the number K of hashes used per vertex, and the number of bits M within the bitfield. The approximate number of bits required for storing N vertices at a desired false positive rate, is given by (Bloom, 1970; Broder and Mitzenmacher, 2003), cf. (1). This yields a space requirement of $\approx$10 bits per vertex for a false positive rate of 1 %, which is much less compared to fully redundant storage. Similar rules hold true for the optimal number of hashes, (Broder and Mitzenmacher, 2003), see (2). With the number of stored bits being dynamic, we can adjust the Bloom filter size to yield a reasonable false positive rate.

$$M \approx -1.44N \log_2(p) \ . \tag{1}$$

$$K = \frac{M}{N} \ln 2 \approx -1.44 \ln(2) \log_2(p) \ . \tag{2}$$

The computational cost of the Bloom filter mainly depends on the performance of the hash algorithms, converting arbitrary data into a numeric value, uniformly throughout the whole range, that is, the size of the bitfield. While 64 bit unsigned integer vertex *ids* already are numeric values, *ids* can not be used as-are, since the bitfield will be much smaller than 2^{64} bits. Yet, a hash function for this kind of input data is much simpler, as it just needs to distribute all potential vertex *ids* uniformly among the available bitfield slots. This is commonly achieved by multiplying the *id* x with some number a_i, limiting the result to the number of slots using the modulo operator:

$$H_i'(x) = y = a_i \cdot x \pmod{M}, \ \ x \in \mathbb{N}, \ \ a_i \in \mathbb{N}_{>0} \ . \tag{3}$$

However, this operator is known to be very costly (Granlund, 2017). Thus we exploit the *residue class ring property* (4). For 64 bit unsigned integer *vertex ids*, which are of base 2, the last k digits of $(x)_2$ are given by applying a bitmask, or *bitwise and*, of $(2^k - 1)$ to $(x)_2$. Following this approach, we can alter (3) by replacing the modulo operator with *bitwise and* while selecting prime numbers for a_i, since they yield best uniformity results (Hull and Dobell, 1962). Therefore, we limit our Bloom filter sizes to $2^k, k \in \mathbb{N}$ and use (5) as our hash algorithm, which we call PrimeHash henceforth.

$$(x)_{\text{base}} \pmod{\text{base}^k} = \text{last } k \text{ digits of } (x)_{\text{base}} \ . \tag{4}$$

$$H_i'(x) = y = (a_i \cdot x) \wedge (M-1) \ . \tag{5}$$

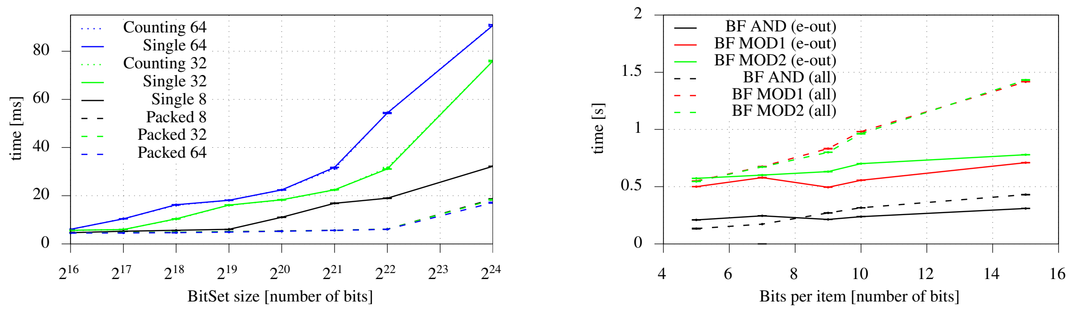
Besides returning false positives, Bloom filters suffers from additional drawbacks that need to be considered: As only single bits are stored, collisions can not be tracked, and vertices can not be deleted from the filter. For dynamic graphs, where many deletions occur, the false positive rate might reach unacceptable levels over time. To overcome collisions ambiguities, the *counting Bloom filter* stores the *number* of elements contributing to each slot. This enables deletion by decreasing the corresponding number, but requires additional memory to store counters instead of bits. Similar to the missing support for deletion, is the lack of runtime scalability. The more vertices are added to the filter, the more bits are set to 1. Eventually, all bits will be set and the filter is useless. As the Bloom filter does not store the vertices themselves, growing is not supported by the data structure on its own, but requires re-scanning the whole graph, rehashing all vertices. To reach an acceptable false positive rate for a given graph, the Bloom filters size, and thus the number of to-be-added vertices, must be known beforehand. Scalable Bloom filters can mitigate this issue, but within this paper we concentrate on static graphs and static Bloom filters, to reduce complexity. This does not limit the applicability of our approach, since static and dynamic graphs share the same messaging procedure, and processing GPM on dynamic graphs would equally benefit from our optimization. A scalable Bloom filter with a dynamic graph would only add to computational complexity, but not to the messaging issue, and is thus ignored.

4 EVALUATION

Our developed GPM engine is a research prototype, which builds upon the DORA, targeting NUMA-SMP systems as mentioned in Section 1. We have tested our GPM engine against three different graphs. One is a bibliographical network, the second represents a social network and the third graph stands for a protein network, where the three are called *biblio*, *social* and *uniprot* respectively henceforth. All three graphs are generated with gMark (Bagan et al., 2017) to consist of approx. 1 M edges each. For our experiments, we store the graphs both with OES and fully redundant (OES+IES), as described in Sections 2 and 3. Our evaluation hardware consists of a four socket NUMA system, each equipped with an Intel(R) Xeon(R) Gold 6130 CPU @ 2.10GHz, resulting in 128 hardware threads with a total of 384 GB of main memory. With this system, we want to examine the messaging behavior between a large number of workers, even if its main memory is a bit over-provisioned for the generated datasets. This section is structured as follows: First, we want to emphasize the necessity of a careful Bloom filter design. Second, we show the benefits and drawbacks of both fully redundant storage versus the Bloom filter optimized storage. Third, we conduct extensive experiments and run the example queries against the aforementioned storage settings, with and without an additionally applied Bloom filter in different parts of our GPM engine. To underline the importance of an appropriate Bloom filter design, we show its read/write performance in Figure 2. Figure 2(a) shows the *write* results for our testing machine. As can be seen, the counting filter from Section 3 yields the same insertion performance as storing only one bit in a larger type, since their points almost overlap for 32 bit or 64 bit data types. Using packed data storage, where each hashed bit is stored using an actual bit within a larger scalar value, proves to be the fastest storage solution. This is most likely due to reduced storage requirements, fitting the internal caches of the CPU. Figure 2(b) proves the superiority of our *bitwise and* based PrimeHash against the traditional modulo operator. In terms of fairness, we ran our experiments for the modulo operator against Bloom filters using the same size as required for PrimeHash (2^x, see Eq. (4)) as well as the exactly calculated size according to Eq. 1. The figure shows, that using *bitwise and* clearly outperforms the modulo variants within both scenarios: always calculating all hash functions according to Eq. (2), or returning after the first *false* (early-out).

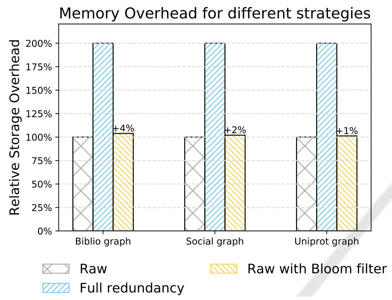
For our graph related experiments, we have used the partitioning strategies as explained in (Krause et al., 2017a). From that paper, we have chosen HashVertices, RoundRobinVertices and Multilevel k-Way partitioning. In summary, the first two partition the graph following their names and the k-Way partitioning is a sophisticated graph partitioning algorithm, which first partitions the graph very coarse grained but later refines the result in subsequent steps. In this paper, we use the METIS 5.1 implementation of that algorithm (Karypis and Kumar, 1998). Furthermore, we have chosen two different graph patterns for our analysis. The query *Q1* forms a rectangle consisting of four vertices and four edges and the query *Q2* represents a V shaped pattern consisting of five vertices and four edges. Both queries have a different amount of backward edges at significant evaluation steps to emphasize their impact. This leads to diverse communicational behavior, which allows us to show the effect of both full redundancy and Bloom filter usage standalone and in combination.

Figure 3(a) depicts the general memory investment for the previously mentioned improvements. The figure shows the relative storage overhead for full redundancy, which is obviously always twice as much as OES, compared to the standard storage. Adding a Bloom filter to the raw storage does not add much in terms of memory needed, however its performance gain can be remarkable. Figure 3(b) shows the result-

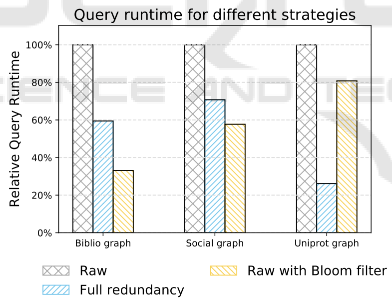


(a) Insert 5 million entries. (b) Query 1 million items.

Figure 2: Time to perform different actions, based on the Bloom filter storage strategy (left) and comparing *bitwise and* [BF AND] vs. the modulo operator [BF MOD1/2] (right). While [BF MOD1] uses the size required by Eq. (4), [BF MOD2] refers to the size from Eq. (1) instead.



(a) Relative storage overhead.



(b) Relative query performance for Q1.

Figure 3: Invested memory vs. gained performance for full redundancy against a Bloom filter within the data partitions, $M = 2^{20}$, k-Way partitioning.

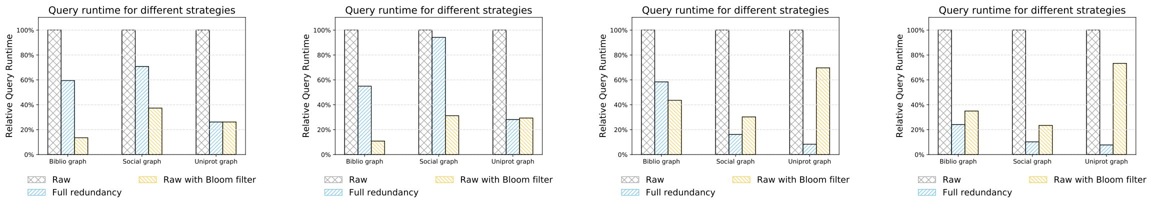
ing query run times for all storage strategies. The raw storage is only the slowest and adding redundancy or a Bloom fitler increases the performance. Interestingly, for the *Biblio* use case, the Bloom filter outperforms even the redundant storage. The reason is, that the Bloom filter can sort out edge requests for target vertices, that are not stored in the partition, which is not covered by redundant storage.

When implementing the Bloom filter, we can do that on multiple locations. Obvious candidates are the data partitions themselves, which makes the Bloom filter behave more like a secondary index. By doing this, the system still needs to activate all workers to find out, if a partition contains a requested vertex. On the other hand, we still exploit all cores to perform the filtering process in parallel. A second possibility is to place the Bloom filter together with the partitioning information. This allows us to directly check, if a certain partition *possibly contains* a requested vertex. The routing based workload reduction can give another performance increase as shown in Figure 4(a), since workers are not unnecessarily activated. However, looking up target partitions is an inherently serial code segment. Thus, iterating over all partition related Bloom filters leads to increased local overhead, which linearly increases with the amount of partitions in the system.

Besides varying the Bloom filter location, we can also swap the underlying partitioning. Figure 4(b) depicts the relative query runtime for routing based workload optimization using the RoundRobinVertices (RRV) partitioning strategy. We observe completely different query performance for both the redundant and Bloom filter supported query execution. In addition, neither the RRV nor the k-Way partitioning strategy yield globally optimal results, which supports our findings from previous work (Krause et al., 2017a). Yet, the Bloom filter approach increases the query performance for both underlying partitionings.

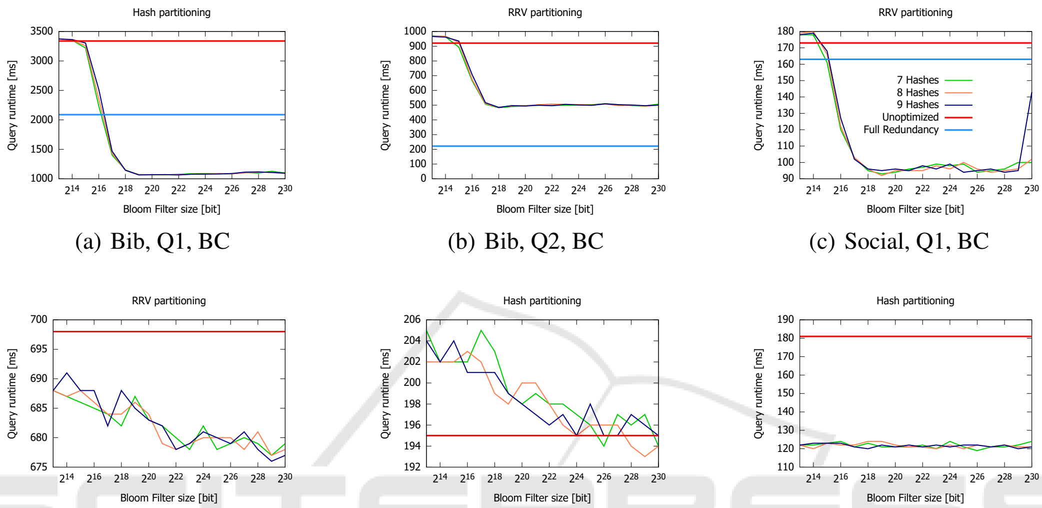
After showing the performance gain for Q1, we now discuss selected results for Q2 in Figure 4. As for Q1, we achieve a performance gain with both the redundant storage as well as the Bloom filter employment. However, here we see a significant difference between the two, at least for the *Uniprot* graph. We identified, that an extraordinarily high amount of intermediate results occurs right before evaluating the backward edge and thus, the aforementioned serial checking of Bloom filter becomes a bottleneck.

Based on these observations, we can state that em-



(a) Q1, k-Way partitioning. (b) Q1, RRV partitioning. (c) Q2, k-Way partitioning. (d) Q2, RRV partitioning.

Figure 4: Relative query performance for different partitioning strategies using the routing based workload reduction, $M = 2^{20}$.



(a) Bib, Q1, BC (b) Bib, Q2, BC (c) Social, Q1, BC

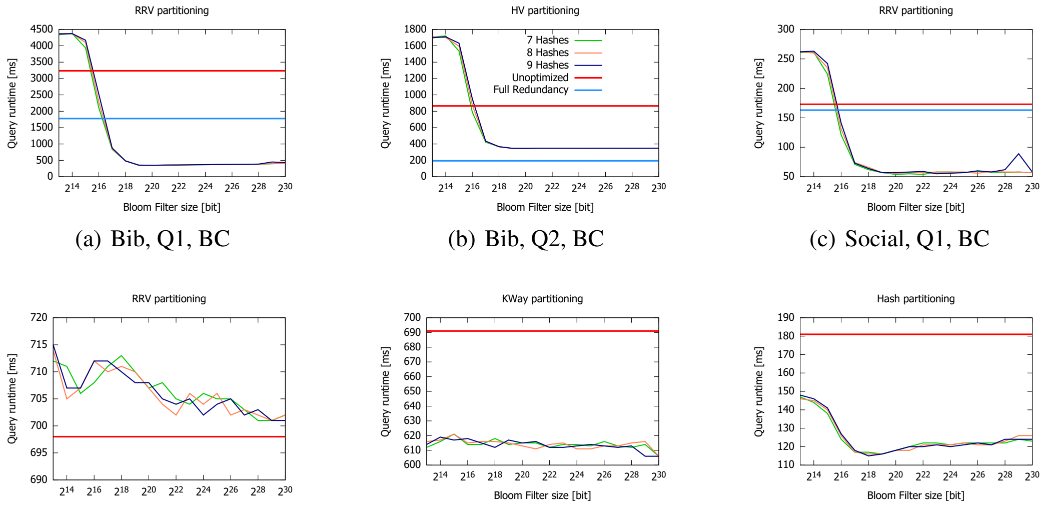
(d) Uni, Q2, UC (e) Bib, Q2, UC (f) Social, Q1, UC

Figure 5: Query Performance with varying Bloom filter parameters, Bloom filter implemented in the data partitions. The baseline denotes the performance without a Bloom filter. BC = Broadcasts with 'OES' as Unoptimized, UC = Unicasts with 'Fully redundant' as Unoptimized

ploying a fixed sized Bloom filter can help to improve query performance with low memory overhead. However, as the performance of the Bloom filter varies with its size M, we conducted various experiments with both partition and routing based Bloom filter implementations. For the experiments in Figure 5, we examined both queries on all mentioned data sets. We have tested the impact of a different number of hash functions against the baseline, where no Bloom filter was used and thus always all workers need to be activated. We will only present selected experiments, due to the large amount of possible experiments. Presented runtimes are the average of 10 runs, without the fastest and the slowest runtime. The first row of Figures 5 and 6 shows selected experiments for the raw storage with only outgoing edges, and the second row applies our Bloom filter on top of the fully redundant storage, to show that combining both strategies can improve our performance even further. Because of the varying runtime between the testing queries and on different graphs, we scaled the Y-axis accordingly for every experiment in Figures 5 and 6.

All figures from Figure 5, except Figure 5(e), clearly show the desired results. That is, the bigger the Bloom filter, the bigger is the performance benefit. Increasing the Bloom filter size is indirectly proportional to the expected false positive rate, thus leading to less unnecessary work. In detail, Figure 5(b) behaves like anticipated. Adding a Bloom filter will increase the performance to allow query runtimes somewhere between the raw storage and the fully redundant storage. On top of that, Figures 5(a) and 5(c) show an improved performance even beyond the fully redundant storage. The same holds true for Figures 5(d) and 5(f). Applying our Bloom filter technique on top of the fully redundant storage leads to an additional performance boost, since the Bloom filter acts as a secondary index structure. By blooming all target vertices for every source vertex in a partition, the Bloom filter can most certainly reject requests for edges with a target vertex, which is not present in the respective partition.

Figure 5(e) is a special case. For smaller Bloom filters, the systems performance is slower than us-



(a) Bib, Q1, BC (b) Bib, Q2, BC (c) Social, Q1, BC

(d) Uni, Q2, UC (e) Bib, Q2, UC (f) Social, Q1, UC

Figure 6: Query Performance with varying Bloom filter parameters, Bloom filter implemented with the partitioning information. The baseline denotes the performance without a Bloom filter. BC = Broadcasts with 'OES' as Unoptimized, UC = Unicasts with 'Fully redundant' as Unoptimized

ing the raw storage. Although the query runtime is consistently decreasing, it barely reaches the baseline performance, where no Bloom filter is used. This behavior can be explained with the amount of broadcasts in the system, when only a small number of partitions contains actual data. Since the Bloom filter is only active, *after* the messages have been sent, we still see the same amount of messages in the system and the overhead of checking the Bloom filter is added on top of it.

For better comparability, Figure 6 shows the same experiments as Figure 5, but with the adjusted Bloom filter location. Most surprising is the observation, that avoiding messages is not generally better. For example, the experiments of Figures 5(d) and 6(d) show a better performance, when messages are filtered out in parallel, instead of avoiding them; the same holds for Figures 5(e) and 6(e) respectively. This effect can be explained with the large serial code segment, which is executed, whenever the Bloom filter is probed. On the other hand, the experiments in Figures 6(a) to 6(c) greatly benefit from the reduced message load. As for Figure 6(f), we can clearly see that there is an optimal Bloom filter size, after which the performance drops, possibly reasoned by the bigger bitfields, which get less cache friendly.

5 RELATED WORK

Graph processing is a wide field with continuously ongoing research. Because of the plethora of use cases, many systems are built to solve a specific problem. A comparable system might be Pregel+ (Yan et al., 2015), which was considered as the fastest graph engine (Lu et al., 2014). In that system, every worker is an MPI process and exchanges messages. Pregel+ leverages vertex mirroring to distribute workload for improved performance, which is orthogonal to our approach of reducing workload. In our evaluation, we showed that redundancy introduces a huge memory overhead for the achieved performance, compared to our Bloom filter approach. A more recent system is Turbograph++ (Ko and Han, 2018), which distributes vertices and edges among multiple machines, where each machine stores the data on disk. The main difference between our system and TurboGraph++ is our processing model. Because of the inherent messaging, our model resembles a streaming engine, where the data flows from one operator to the next, where invalid intermediate results get pruned on the fly. The authors of (Neumann and Weikum, 2009) use a Bloom filter to avoid constructing full semi-join tables on RDF data graphs, whereas our approach uses a Bloom filter to completely eliminate the need to touch a whole data partition.

6 CONCLUSION

In this paper we have presented measures for trading storage overhead for workload reduction. Our key findings were, that despite being more accurate, fully redundant storage does not yield proportional performance gain, compared to the memory invested. We could show in our evaluation, that our hand tuned Bloom filter approach can save a tremendous amount of main memory and still provide reasonable speedups. Considering the huge experimental space, we envision to continue this research and combine these findings with (Krause et al., 2017a), to built an adaptive system, which can adapt both the partitioning and the employed Bloom filter to achieve optimal performance.

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