Spatter: A Benchmark Suite for Evaluating Sparse Access Patterns

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Abstract—Recent characterizations of data movement performance have evaluated optimizations for dense and blocked accesses used by accelerators like GPUs and Xeon Phi, but sparse access patterns like scatter and gather are still not well understood across current and emerging architectures. We propose a tunable benchmark suite, Spatter, that allows users to characterize scatter, gather, and related sparse access patterns at a low level across multiple backends, including CUDA, OpenCL, and OpenMP. Spatter also allows users to vary the block size and amount of data that is moved to create a more comprehensive picture of sparse access patterns and to model patterns that are found in real applications.

With Spatter we aim to characterize the performance of memory systems in a novel way by evaluating how the density of accesses compares against real-world effective memory bandwidths (measured by STREAM) and how it can be compared across widely varying architectures including GPUs and x86, ARM, and Power CPUs. We demonstrate how Spatter can be used to generate analysis plots comparing different architectures and show that current GPU systems achieve up to 65% of STREAM bandwidth for sparse accesses and are more energy efficient in doing so for several different sparsity patterns. Our future plans for the spatter benchmark are to use these results to predict the impact of new memory access primitives on various architectures, develop backends for novel hardware like FPGAs and the Emu Chick, and automate testing so that users can perform their own sparse access studies.

I. INTRODUCTION

For some time now off-chip memory has been a major bottleneck in high-performance computer systems. CPUs gain processing capacity through increasing core counts and wider vector units while memory latency stays stable and bandwidth grows slowly. Increasingly complex cache hierarchies ease this problem for applications with regular memory accesses and large amounts of locality. High-bandwidth memory relies on increasing access granularity to improve bandwidth. However, there are many programs which do not display regular memory patterns and have low data locality and thus do not benefit from these advances. Irregular applications including many data analysis methods based on sparse matrix and graph algorithms read and write scattered data, leading to low bandwidth utilization. These applications need new approaches in memory system design. Guiding these approaches requires careful characterization of memory system behavior for irregular data analysis applications.

We present a new benchmark suite, Spatter, that covers sparse access patterns representing a variety of applications across different language and architecture platforms. Spatter’s measurements characterize how these applications memory access patterns aperform on today’s hardware platforms, guiding decisions on future platforms. More specifically, Spatter provides the following:

- A highly tunable scatter/gather with knobs for adjusting thread block size and ILP on GPUs and block size for multiple platforms.
- CUDA, OpenMP, and OpenCL backends.
- Semi-automated testing and R-based plotting scripts that run a sweep of strided accesses with multiple parameters and then plot the best results in a STREAM-like fashion.
- Comparison tools for plotting the percentage of effective bandwidth that is achieved as compared to results from either the STREAM or BabelStream benchmark suites.
- The capability to plot sparsity patterns for a single architecture or compare multiple architectures.
- Scripts to run “random access” scatter/gather experiments that are demonstrated and compared with traditional scatter/gather experiments.

The current Spatter benchmark results show that newer GPU architectures perform best for both scatter and gather operations at lower sparsity values with peak effective sparse bandwidth rates of close to 65%, and their performance also degrades more slowly when compared to CPU- and KNL-based systems. Meanwhile, the Power8 system performs best of all the CPU-based platforms both for strided accesses and random access experiments. In terms of energy efficiency, the GV100 Volta GPU is shown to have the highest peak efficiency of the tested platforms with over 1500 Bytes transferred per Joule.

II. RELATED WORK

Our aim for Spatter is to measure at a low level the effects of sparsity and indirect accesses on effective bandwidth for a particular application or algorithm. While a number of bandwidth-related benchmarks exist, there are no current suites that explicitly support granular examinations of sparse memory accesses. The closest analogue to our work is APEX-Map [1], which allows for varying sparsity to control the amount of spatial locality in the tested data set. However, APEX-map...
has not been updated for heterogeneous devices and does not currently seem to be maintained.

In terms of peak effective, or real-world achievable bandwidth, the STREAM benchmark [2] provides the most widely used measurement of sustained local memory bandwidth using a regular, linear data access pattern. Similarly, GPU-Stream 2.0, aka BabelStream [3], out of University of Bristol provides a STREAM interface for heterogeneous devices using multiple backends like OpenMP, CUDA, OpenCL, SyCL, Kokkos, and Raja. Both of these benchmarks provide similar bandwidth numbers on CPU-based systems, but neither suite supports strided access patterns across multiple backends and architectures.

Pointer chasing benchmarks [4] measure the effects of memory latency but are limited in scope. Additionally, they amplify the effects of memory latency. We are interested in a single indirection per reference, while the entire point of pointer chasing is to follow many levels of indirection. Pointer chasing does not capture the scope of a scatter-type operation. In this vein, the RandomAccess benchmark, available in the HPC Challenge Benchmark Suite [5] measures more complex memory access patterns than STREAM, but does not model sparsity.

A. Heterogeneous Architectural Benchmarking

Memory access patterns have been studied extensively on heterogeneous and distributed memory machines, where data movement has been a concern for a long time. Benchmarks such as SHOC [6], Parboil [7], and Rodinia [8] provide varying levels of memory access patterns that critical to HPC applications. For example, SHOC contains “Level 0” DeviceMemory and BusSpeedDownload benchmarks that can be used to characterize GPUs and some CPU-based devices. The design of Spatter is intended to create a new benchmark suite with a more focused set of access patterns to supplement these existing benchmark suites and to provide a simpler mechanism for comparing scatter and gather operations across programming models and architectures.

Other work focuses on optimizing memory access patterns for tough-to-program heterogeneous devices like GPUs. Dymaxion [9] takes an API approach to transforming data layouts and data structures and looks at scatter and gather as part of a sparse matrix-vector multiplication kernel experiment. Jang, et al. [10] characterize loop body random and complex memory access patterns and attempt to resolve them into simpler and regular patterns that can be easily vectorized with GPU programming languages. Finally, CuMAPz [11] provides a tool to evaluate different optimization techniques for CUDA programs with a specific focus on access patterns for shared and global memory.

B. Extensions to Other Architectures

One initial motivation for this work is to better implement sparse accesses patterns on nontraditional accelerators like FPGAs and the Emu Chick. For FPGAs, the Spector FPGA Suite [12] provides several features that have influenced the design of our benchmark suite. Spector uses OpenCL-based High-Level Synthesis and compiles a number of different FPGA kernels with various parameters and then attempts to pick the best configuration to execute on a specific FPGA device. While this process can be time-consuming for FPGAs due to routing heuristics, it does provide some motivation for the design of Spatter. As shown in Section III, we design scripts that run multiple tests and then pick the best result for a given work item size, block size, and vector length to plot as the “best” result for a particular scatter/gather operation.

Finally, there is also work in computer architecture that explores the area of adding more capabilities to vector units. SuperStrider [13] and Arm’s Scalable Vector Extension [14] both aim to implement some type of Scatter/gather operation in hardware. Similarly, the Emu system [15] focuses on improving random memory accesses by moving lightweight threads to the data in remote DRAM. Spatter complements these hardware designs and associated benchmarking by allowing users to test how their code can benefit from dedicated data rearrangement units or data migration strategies. These projects primarily focus on architectural simulation and emulation, while we are looking at approaches to create effective sparse kernels that can be tested on FPGA prototypes or with these new Architectures.

III. DESIGN OF THE SPATTER BENCHMARK

The Spatter benchmark suite takes into consideration several features that are critical to tuning the performance of a scatter/gather operation. We provide an overview of the key features of Spatter and related tools for running experiments.

![Fig. 1: Combined Scatter/Gather](image)

**Amount of data moved:** Like STREAM, the Spatter benchmark specifies a certain number of elements (usually doubles) to be moved from a dense source space to a sparser target space. As Figure 1 shows for a combined scatter/gather operation, an intermediate vector $i$ selects elements from the source, $X$ and the vector $j$ stores the destinations for these elements in $Y$. $i$ and $j$ must be the same length, but the use of two arrays allows for future extensions to more complex (e.g., dynamic stride) mappings to a sparse target space.

As with STREAM, it is important to use a large source buffer size so that any possible caching or prefetching optimizations are minimized as much as possible. As discussed in Section IV, we typically run Spatter with $2^{22}$ elements (32 MB source array). Spatter also allows for running experiments...
with a randomized index array to simulate a more irregular “random access” scatter/gather more similar to GUPS [5] or pointer chasing benchmarks [4] rather than the default strided pattern. In this randomized mode, the regular strided indices are generated first, and then they are shuffled with the Fish-er-Yates algorithm [16]. 64-bit random indices are generated with a Mersenne twister [17].

**Sparsity:** While we would eventually like to support function-based sparse access patterns (e.g., a dynamic stride) as proposed by APIs like SPDRE [18], our run scripts currently support strided concurrency. For the experiments in this paper, we demonstrate access patterns with a stride of 1 up to a stride of 128 or a target space that has 127 empty elements between each mapped target element.

**Supported Backends:** Spatter currently supports three backends - CUDA, OpenCL, and OpenMP. The CUDA and OpenCL implementations have optimizations to specify different vector widths while the OpenMP implementation supports basic SIMD pragmas (OpenMP 4.0). When comparing results to determine effective sparse bandwidth (Section IV-A), Spatter results are compared with a similar STREAM copy result from BabelStream’s OpenCL, CUDA, or OpenMP implementations. We discuss future extensions for FPGAs and the Emu Chick in Section VII.

### A. Runtime Configuration Features

**Vector width or unit of work per thread:** Due to Little’s Law, we understand that we need to have enough concurrency available to hide latency. In GPUs, we tend to increase the available concurrency by increasing occupancy. While this will work, it is not the only source of concurrency in GPUs. We can also provide the required concurrency through instruction-level parallelism. This is exposed in the benchmark by having a single thread or work-item move multiple elements. OpenCL supports vector types, which help optimize this case. CUDA and OpenMP, however, accomplish this using constant-size loops.

**Thread Block Size** In GPUs, it is important to pick a good thread block size if you want to get good performance, as GPUs can support thousands of threads per SM, but only a relatively few thread blocks. Our benchmark tests with several thread blocks sizes, and our scripts plots the best configuration. Since this benchmark only moves data, we found that small thread block sizes were enough to saturate the available memory bandwidth, and thus we only check block sizes from 1 to 16.

**Miscellaneous features:**

**Cache Residency** The benchmark can be configured to use multiple “worksets” meaning multiple copies of the data and index buffers. The benchmark will then use a different workset for each execution, hopefully removing some caching effects for smaller datasets.

**Validation** The code has a validate flag so that any changes to optimized kernels are checked against a serial, CPU version of the kernels for correctness.

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**Simplified Parameters** As one may imagine from the description, the benchmark supports quite a few run-time options. This can make running even simple tests rather burdensome on the user. Spatter will make intelligent guesses about the backend to be used and the device to run on but still requires the user to specify the amount of data to move. It also informs the user about the guesses it is making, though this output can be silenced.

### B. Execution Scripts and Plotting

Spatter is compiled using CMake and then is run either by calling the executable with at least a length (amount of data to be moved) and optionally a backend language, device, and platform (for OpenCL). As Listing 1 shows, a simple Spatter run can be run by specifying just a few simple command-line parameters.

**Listing 1: Spatter Execution**

```bash
# Run scatter with 4194304 elements, stride of 2, and vector width of 4.
./spatter -i 4194304 -s 2 -k scatter -v 4
```

Warning: No backend specified, guessing OpenMP
Warning: Kernel file unspecified, guessing kernels/
kernel_vector.cl backend kernel op time source_size target_size idx_size \ worksets bytesMoved usable_bandwidth omp_threads
vector_len block_dim

**Listing 2: Spatter Scripts**

```bash
# Run a sweep over common parameters with the OpenMP backend
# for scatter, gather, and scatter/gather and label results
./sg-sparse-roofline.sh openmp broadwell-cpu
```

Finally, the Spatter benchmark suite provides R and ggplot2[19] based scripts that plot the output from individual Spatter runs or the output from included sweep scripts. The results in this paper are generated primarily with these scripts, and a future goal is to provide an automated path for a user to download the tool suite, compile, run a set of sweep tests, and then easily generate a set of informative plots.

### IV. Experimental Setup

**A. Metrics for Performance**

While STREAM provides basic min, max, and average measurements for memory bandwidth in MB/s, we focus on...
A different metric, **effective sparse bandwidth** to determine how well a system can perform scatter and gather operations. Effective sparse bandwidth specifically refers to the amount of achievable bandwidth (i.e., measured by STREAM) that can be measured for a specific test configuration. For example, if STREAM bandwidth is 30,000 MB/s and our measured bandwidth for sparsity=1/2 is 15,000 MB/s, we report that our effective sparse bandwidth is 50%. This metric allows us to compare systems where the maximum STREAM bandwidths may be very different and to provide insights into how architectures or programming models differ with different amounts of sparsity. An important note, however, is that we do not include bandwidth used by our index buffers in the bandwidth calculation. If you wish to consider that data as well, you can multiply the bandwidths by 1.5, as an index buffer is as large as the amount of data moved, but is only read.

**B. Experimental Test Systems and Configurations**

Each run of the Spatter benchmark uses the maximum bandwidth of 10 runs. STREAM results for calculating effective sparse bandwidth are generated using $2^{25}$ elements while all Spatter tests are run with a dense array of $2^{22}$ elements or $2^{25}$ bytes (32 MB) as the source array. As mentioned in Section III-B, the plotting scripts that are used allow us to plot the best run from a sweep of all the possible runtime parameters.

To control for NUMA effects, CPU systems are tested using all the cores on one socket or one NUMA region if the system has more than one CPU socket. We primarily run this configuration because some of our test systems like the ARM ThunderX2 prototype have some possible hardware bugs with access across NUMA regions. This means that the KNL is run using all the threads in one NUMA region and by default it targets the local DDR4 with a peak bandwidth of 90 GB/s (future work will look at the use of the MCDRAM for Spatter). For all the OpenMP tests, the following environment parameters are used:

- `OMP_NUM_THREADS=<num_threads_single_socket>`
- `OMP_PROC_BIND=master`
- `OMP_PLACES=sockets`
- `KMP_AFFINITY=compact (for the KNL only)`

Table I shows the difference configurations and backends tested for our initial evaluation using the Spatter benchmark suite. We pick a diverse set of systems based on what is currently available in our lab and collaborator’s research labs, including a standalone Knight’s Landing system, a Power8 S21LC system (S821LC-8001-12C), and a prototype HPE Apollo system with ARMv8 ThunderX2 chips designed by Cavium. We also include a server-grade and desktop-grade Intel CPU system and several generations of NVIDIA GPUs. Unfortunately we currently do not have access to a recent AMD GPU, CPU, or APU system for testing Spatter.

STREAM results are reported for each platform based on BabelStream runs with default parameters that match the same parameters for Spatter experiments. While in some cases this STREAM bandwidth does not match closely with the “ideal” STREAM bandwidth (e.g., 593 GB/s for the GV100 versus 870 GB/s for ideal STREAM bandwidth), this value is listed as a fair comparison value for our plots that is measured on our selected configurations. Additionally, some systems like Power8 and KNL may require additional tuning in future experiments to use the full bandwidth of the Centaur memory controller (Power8) or to run exclusively using MCDRAM (on KNL). Power results are TDP values that are pulled from public sources for each GPU, CPU, and KNL device or tools like `nvidia-smi` for GPUs. Power8 results use the IBM System Energy Estimator to determine the TDP of our Power8 CPU [20].

### V. Results

#### A. Comparing Architectures

Figures 2, 3, and 4 demonstrate two different ways that Spatter results can be analyzed and plotted to investigate the performance characteristics of scatter and gather operations on different architectures as well as a suggested "STREAM-like" analysis that allows for a high-level comparison of the maximum effective sparse bandwidth for different architectures (Figures 3 and 4).

The grid in Figure 2 demonstrates the basic plotting output of the Spatter benchmark suite and plotting script with effective sparse bandwidth curves plotted on the Y axis relative to the BabelStream bandwidth and work per thread plotted on the X axis. For the dense case (sparsity=1), architectures that can use a CUDA or OpenCL backend like the P100 will have a variable amount of bandwidth as the amount of work per thread is increased. In both the scatter and gather cases, peak effective sparse bandwidth is achieved for the dense case with 4 to 8 elements gathered or scattered per thread. As the
sparsity increases past 1/4 the benefits of increased work per thread become much less pronounced.

The Broadwell and the Power8 systems demonstrate bandwidth curves that are much less variable since OpenMP pragmas provide very basic hints as to how to vectorize scatter/gather operations when compared to more explicit vectorization strategies used in the CUDA and OpenCL backends. The Power8 system demonstrates high effective sparse bandwidth for both the dense and sparsity=1/2 case, although it also has a reasonably low STREAM bandwidth due to usage of only one of the 4 available memory channels with default test settings.

Figure 3 demonstrates a high-level evaluation of the scatter and gather characteristics of each of the nine test platforms with the best result being plotted for each sparsity setting on the X axis. While some of the CPU systems with high memory bandwidth (e.g. TX2) suffer from low effective sparse bandwidth with peak effective bandwidths of 30%, the GPU platforms typically are able to perform scatter and gather at high fractions of the available STREAM bandwidth from 65% for sparsity=1 to 20% for sparsity=1/32. The Cavium TX2 is the worst performing architecture for both scatter and gather with a peak effective bandwidth of 33% for gather and 5% of bandwidth for sparsity=1/32.

The OpenCL backend results in Figure 4 more clearly show the separation between GPUs and CPU-based architectures at lower sparsity values and for gather at very sparse access granularities. Interestingly, both the Titan XP and the P100 GPU are able to achieve about 30% effective bandwidth at sparsity=1/32.

B. Comparing Backends

Figure 5 demonstrates absolute scatter performance using both the CUDA and OpenCL backends. While the CUDA backend exhibits slightly higher bandwidth, we note that both sets of tests demonstrate remarkably consistent trend lines and have approximately equal absolute or effective bandwidths as the work per thread is increased. This similarity can be partially attributed to the relatively simple nature of these low-level scatter and gather kernels and the similarities of OpenCL and CUDA implementation, but these results show that comparable measurements can be made with either the CUDA or OpenCL backend with GPU platforms.

Using the OpenCL and OpenMP backends, we compare the Broadwell CPU platform for scatter operations in Figure 6. The plots for these experiments demonstrate that OpenMP can
more easily achieve a higher peak effective bandwidth than OpenCL and that the bandwidth provided does not vary with as the work per thread is increased. As mentioned previously, the variation in performance for the OpenCL tests are closely related to the optimal amount of work per thread, which differs between architectures. Likewise, the OpenMP results show no variation because the simple parallel for and simd pragmas used are not effectively able to vectorize the scatter operation without additional hints from the user.

C. Randomized Accesses

The results in Figure 7 show the results for gather experiments using the random indices permutation described in Section III. Figure 7a shows that GPU architectures (excepting GV100) can only achieve at best 20% effective sparse bandwidth but that sparsity does not appreciably decrease bandwidth any further. The data for CPU and KNL systems (Figure 7b) show much variation with the Power8 being a high-performing outlier for the dense case and with KNL also performing well when compared to other CPU-based systems. The Sandy Bridge CPU system and TX2 platform both achieve very low effective sparse bandwidths as sparsity increases, falling to minimums of 5% and 2.3% of the their peak bandwidths.

When compared with the plots in Figure 3a, we see just how much of an impact randomness has. For instance, if we consider the Broadwell CPU, we see that it can attain 15% of peak with a strided access pattern and a sparsity of 1/4, but if given a random pattern it can only attain this fraction of peak with a sparsity of 1/2.

D. Energy Efficiency

The gather and scatter results shown in Figures 8a and 8b use the TDP values from Table I along with Spatter measurements to plot the power efficiency of each tested platform in terms of Bytes transferred/Joule. For both gather and scatter, the newer GPU systems have a very high performance/energy ratio with a peak of 1560 B/Joule for the Volta GV100 GPU. These plots also demonstrate the memory system and power efficiency improvements that have been made in the design of newer GPUs since the the Kepler K40, which has a trend line much closer to the KNL and CPU-based systems.

VI. DISCUSSION

The results from our initial Spatter benchmarking should not be considered conclusive as to which system is best for sparse operations like scatter/gather, but they do point to a few key initial insights that can be used to guide further explorations.

Overall, newer GPU systems show a separation from CPU and KNL systems in terms of (1) peak effective sparse bandwidth, (2) performance degradation as sparsity increases, and (3) energy efficiency. Some speculation that would require further experimentation and profiling might be that GPUs are good at coalescing strided loads to some extent or that each SM "core" has limited cache and thus suffers a smaller performance hit with sparse accesses. In fact, the results from the random indices experiments (Figure 7a) indicate that both of these hardware features might play a role, as GPUs show a consistent lower bound of effective sparse bandwidth (that does not vary with sparsity) whereas CPUs continue to suffer performance penalties as sparsity increases.

For CPU-based Spatter results, it is interesting to see that the Power8 system performs very well when compared to its
"peak" STREAM bandwidth while the new ARM-based TX2 system seems to underperform compared to the other CPU and KNL systems. Some of these differences can be attributed to the low STREAM bandwidth for the Power8 system (due to our OpenMP settings using only one channel with the Power chip’s Centaur memory controller) and the very high bandwidth of the TX2 system. However, it may also be useful to further investigate the effects of additional OpenMP directives to tune for vector widths, and to test whether or not using newer 512-bit ARM Scalable Vector Extensions (as opposed to the current 128-bit NEON vector extensions) can help improve the performance of scatter and gather. These results show the limitations of a simple benchmark like Spatter; while we can perform a relatively equal comparison between architectures, it may require further optimizations like vectorization and investigation of cache bypass techniques, like non-temporal stores [21], to determine how suitable a platform is for sparse and irregular accesses.

Finally, our initial tests with Spatter demonstrate that while there are some performance differences between backends, the general characteristics of CUDA versus OpenCL scatter/gather and even some OpenCL/OpenMP experiments show the same trend lines and performance curves across backends. While this is not necessarily the case for more complex algorithms and applications, it is useful to observe that at a fundamental level each of these backends can accurately measure and correlate the characteristics of scatter/gather operations.

VII. FUTURE WORK

We envision that the Spatter benchmark will provide a basis for examining common sparse operations across multiple architectures and programming languages. To further this effort, we plan to expand the benchmark suite with the following features: 1) support for new backends and devices, 2) improved automation of tests and parameter selection, and 3) additional variations of sparse patterns to support algorithm and application design.

We plan to provide improved support for novel architectures using backend features like OpenMP 4.5 target pragmas for GPUs, but we are also interested in supporting benchmarking on FPGAs and novel systems like the Emu Chick[4]. These two platforms will require specific implementations using OpenCL/SyCL and Cilk, respectively. In addition, we aim to optimize for CPU architectures explicitly by looking at incorporating hints for prefetching and including support for non-temporal or streaming stores, which is used with STREAM on platforms like the KNL.

In terms of improved testing, we have started to automate some of the testing and graphing process. Our goal in the future is to have users clone the Spatter repository, configure and build, and then run a single script that will pull and run BabelStream, run one of more of our sweep scripts, and plot the results.

Most importantly, we are looking to expand our benchmarking of sparse algorithms by adding variations on scatter and gather including intermediate computation and dynamic access patterns. For example, the BLIS linear algebra library reduces its tuning space by gathering regularly strided data into a sequential buffer, computing, and then scattering to the output space[22]. Similarly, solvers like SuperLU[23] perform scatter/gather operations with dynamic access patterns based on the matrix structure. Extending the patterns that are supported by Spatter will help users more closely characterize kernels that appear repeatedly in HPC applications.
Fig. 5: P100 CUDA vs. OpenCL Scatter Absolute Bandwidth

Fig. 6: Broadwell OpenCL vs. OpenMP Scatter Absolute Bandwidth
Fig. 7: CUDA and OpenMP Random Access

Fig. 8: OpenMP and CUDA Power for Scatter and Gather
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