

Entropy Maximization in Sparse Matrix by Vector Multiplication ($\max_E \text{SpMV}$)

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The peak performance of any SpMV depends primarily on the available memory bandwidth and the capability to use it effectively. GPUs, ASICs, and new FPGAs have higher and higher bandwidth; however, for large scale and highly sparse matrices we find still difficult utilizing this bandwidth because the SpMV random access pattern and workload imbalance. We propose a matrix permutation pre-processing step that aims to maximize the entropy of the distribution of the nonzero elements. We seek any permutation that uniformly distributes the non-zero elements' distribution, thereby generating a SpMV problem that is amenable to work load balancing or to speed up sort algorithms. We conjecture these permutations would be most effective for matrices with no dense rows or columns and, as in preconditioning, when the matrix is reused. We shall show that entropy maximization is an optimization that any architecture may take advantage although in different ways. Most importantly, any developer can consider and deploy. We shall present cases where we can improve performance by 15% on AMD-based systems.

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1 INTRODUCTION

To define the scope of this work, the obvious questions to ask are: first, what randomization or entropy maximization is in the context of sparse matrices; second, why would we use it; third, when it does work. We shall provide formal definitions in the following sections. Briefly, we will permute randomly the rows and columns of a sparse matrix before multiplying it with a dense vector (SpMV) with the aim of speeding this operation. Undoubtedly, this scheme requires some restrictions about the matrix structure, one among them is that it has no or few dense columns or rows. In the case, where there are dense columns or rows, a sparse/dense partitioning scheme should be used. For the remainder of this manuscript, we shall assume the former nonzero structure. We use randomization because it is the poor man's way for preconditioning SpMV in our context, and we do not mean it in a pejorative sense.

Preconditioning speeds up the convergence rate of an iterative linear solver by linearly transforming the associated matrix into a form that affords a faster reduction of the residual error at every iteration. The cost of this transformation is justified by the runtime reduction it affords. Likewise, we foresee randomization playing a similar role for SpMV in the context of iterative linear solvers and other methods (e.g. in convolutions) where the matrix is reused.

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Sparse linear algebra and GraphBLAS kernels are memory bound and there is a common thread in the scientific computing community to develop acceleration libraries mostly for multi-core systems. These predominantly include multi-core processors and GPUs. The goal is a balanced work distribution and, when applicable, minimal communication [6, 11]. When storage strategy and algorithms must be considered together then GPUs provide the work horse for abundant thrust in research [1]. These works aim at optimal solutions and strive for a clear and complete understanding/exploitation of the software-hardware interface; usually the hardware is composed of symmetric computational units. Interestingly, the SpMV's space and time complexity, which are small, may not warrant more performance because we typically end up utilizing only one-thousandth fraction of the available hardware capacity.

The peak performance of any SpMV accelerator depends primarily on the available memory bandwidth (i.e., DRAM such as DDR or HBM) and the capability of the accelerator to effectively use it. Because SpMV is memory-bound, a more important metric than peak performance alone is the fraction of bandwidth utilized, which captures the overall efficiency of the architecture. GPU platforms exhibit very high bandwidth, see the experimental Section 8: Ellesmere DDR5 224GB/s, Fiji HBM 512GB/s, and Vega 20 HBM 1TB/s. Although utilizing this much bandwidth efficiently is difficult for large scale and highly sparse matrices due to very high random access pattern. Custom architectures based on FPGA or ASIC devices can maximize bandwidth utilization by highly customized data-paths and memory hierarchy designs [3, 4, 13]. Most of the existing accelerators saturate the relatively low memory bandwidth available on FPGA platforms (less than 80 GB/s) [3, 4, 8, 10, 12, 13]. Modern FPGA platforms have multiple HBM stacks to provide large memory bandwidth. However, there is no implementation (currently available) that saturates all of the available DRAM bandwidth for SpMV kernel on HBM-enabled FPGA platforms. Scalability of accelerator design remains a major concern, and it is an active area of research.

FPGA platforms used in early works exhibit low peak performance due to the scarcity of external memory bandwidth [3, 7, 14]. For example, Microsoft's implementation of SpMV uses an FPGA platform which only has 2 DDR2-400 memory banks with a resulting bandwidth of 6.4 GB/s [7]. The accelerator is running at 100 MHz, it reads 64 Bytes of data every cycle, which corresponds to 5 non-zeros at every cycle (a non-zero is about 12 Bytes). At best, the peak performance is 10 double precision operations every cycle at 100 MHz, which is 1 GFLOPS (only). In 2009, Convey systems Inc. released the Convey HC-1 FPGA platform. It has 16 DDR2-677 memories resulting in overall 80 GB/s memory bandwidth [10]. The accelerator logic runs at 150 MHz. It consumes 512 Bytes of data every cycle, which corresponds to around 40 non-zeros every cycle. At best, the peak performance is 80 double precision operations every cycle at 150 MHz, which is 12 GFLOPS.

One of the key building blocks for custom architecture solutions is a multi-ported buffer used to storing vector entries [3]. During execution, multiple column indices are used as addresses to read corresponding vector entries; we shall provide more details about the application in Section 2. Designing a buffer with a very large number of read ports is challenging. One solution is *banking* as a mechanism to store partitioned vector entries. Although banking could allow very high throughput indexing unless the same entry is required multiple times and its reads are purely sequential causing loss of bandwidth. For example, hashing techniques and data duplication are possible solutions for this problem. However, another issue arises: When we distribute SpMV computations across p -nodes, some of the nodes, say k , finish later than the rest because of unbalanced work loads (i.e., number of nonzero element) in row/column major traversal. This is a common phenomena for matrices where few rows or columns are dense. These k nodes are referred to as *laggard nodes*. By applying random permutation of columns/rows, we are attempting to balance the loads across all p workers so that there are no laggards. From this hardware vantage point, randomization or

maximizing the entropy of the non-zero element distribution is an optimization transform and provides a clear context for our work.

Clearly, optimally accelerating SpMV is a hard many-parameters optimization problem dependent on the choice of algorithm, data structures, and dedicated hardware (CPU, GPUs, FPGA's, Custom ASIC's). Rather, our goal is to provide a tool, we may say a naive tool, to help understand how the structure of the matrix may affect the HW-SW solution. For the readers in the field of algorithms, SpMV can be mapped into a sorting algorithm. For example, finding elements $x_{i,j}$ and $x_{i,k>j}$ in a sparse matrix requires to find row i and then columns j and k . Sorting is a method to find if an element is in a list with no prior or limited knowledge of its contents. Sorting can be used to prepare the matrix and to find elements in between sparse matrices and sparse vectors. In custom architectures, sorting networks are used to route matrix and vector elements to functional units. In a sense, if one is stuck with a sorting algorithm and a poor distribution, randomization may alter the distribution and throttle performance. Interestingly, the best sorting algorithm is a function of the distribution of the elements [5, 9].

We organize this work as follows: In Section 2, we define the matrix by vector operation; in Section 3, we define what we mean by randomization or entropy maximization. We use randomization to create a uniform distribution in Section 5 and measure uniformity by entropy in Section 4. We present how we drive our experiments to show the effects of randomization in Section 6. In the last sections, we present a summary of the results: we present our work loads for the given benchmarks in Section 7, and the complete set of measures for an AMD CPU and GPUs systems in Section 8.

2 BASIC NOTATIONS

Let us start by describing the basic notations so we can clear the obvious (or not). A Sparse-matrix by vector multiplication $SpMV$ on an (semi) ring based on the operations $(+, *)$ is defined as $\mathbf{y} = \mathbb{M}\mathbf{x}$ so that $y_i = \sum_j M_{i,j} * y_j$ where $M_{i,j}=0$ are not represented nor stored. Most of the experimental results in Section 8 are based on the classic addition $(+)$ and multiplication $(*)$ in floating point precision using 64 bits (i.e., double floating point precision) albeit are extensible to other semi-rings. For instance, it is well known that SpMV defined on the semi-ring $(\min, +)$ is a kernel in computing an all-pairs shortest paths starting with a graph adjacency matrix, and in using a Boolean algebra we can check if two nodes are connected, which is slightly simpler.

We identify a sparse matrix \mathbb{M} of size $M \times N$ as having $O(M + N)$ non-zero elements, number of non zero nnz . Thus the complexity of $\mathbb{M}\mathbf{x}$ is $O(M + N) \approx 2nnz$. Also, we must read at least nnz elements and thus the complexity is $\Theta(M + N) \approx nnz$. We can appreciate that reading the data is as complex as the overall operation. Of course, the definition of sparsity may vary. We represent the matrix \mathbb{M} by using the coordinate list COO or and the compressed sparse row CSR¹ formats. The COO represents the non-zero of a matrix by a triplet (i, j, v) ; very often there are three identical-in-size vectors for the ROW, COLUMN, and VALUE. The COO format takes $3 \times nnz$ space and two consecutive elements in the value array are not bound to be neither in the same row nor column. In fact, we know only that $VALUE[i] = M_{ROW[i], COLUMN[i]}$.

The CSR format stores elements in the same row and with increasing column values consecutively. There are three arrays V, COL, and ROW. The ROW is sorted in increasing order. Its size is M , and $ROW[i]$ is an index in V and COL describing where i -th row starts (i.e., if row i exists). Accordingly, $M_{i,*}$ is stored in $V[ROW[i] : ROW[i+1]]$. The column indices are stored at $COL[ROW[i] : ROW[i+1]]$ and sorted increasingly. The CSR format takes $2 \times nnz + M$ space and a row vector of the matrix can be found in $O(1)$.

¹a.k.a. Compressed row storage CRS.

The computation $y_i = \sum_j M_{i,j} * x_j$ is a sequence of scalar products and, using the CSR format, is computed as follows:

$$Index = ROW[i] : ROW[i + 1]$$

$$y_i = \sum_{\ell \in Index} V[\ell] * x_{COL[\ell]}$$

The matrix row is contiguous (in memory) and rows are stored in increasing order. However, the access of the dense vector \mathbf{x} has no particular pattern, well increasing.

The COO format can be endowed with certain properties. For example, we can sort the array by row and add row information to achieve the same properties of CSR. In contrast, transposing a "sorted" COO matrix simply entails swapping of the arrays ROW and COL. Think about matrix multiply (one of us does constantly). Each scalar product achieves peak performance if the reads of the vector \mathbf{x} are streamlined as much as possible and so the reads of the vector V . If we have multiple cores, each could compute a subset of the y_i and a clean data load balancing can go a long way. If we have few functional units, we would like to have a constant stream of independent $*$ and $+$ operations but with data already in registers. That is, data pre-fetch will go a long way especially for $x_{COL[i]}$, which may have an irregular pattern.

3 RANDOMIZATION AND ENTROPY MAXIMIZATION

We define *Randomization* as row or column permutation transform of the matrix \mathbb{M} (thus a permutation of \mathbf{y} and \mathbf{x}), and we choose these by a pseudo-random process. The obvious question to ask is why should we seek randomization transform? The sparsity of a given matrix \mathbb{M} has a non-zero element distribution induced by the nature of the original problem or by some imposed ordering on the respective nodes of its associated graph. This distribution may be computationally incompatible with the chosen algorithm or architecture. For instance, it can induce some load imbalance in the computation. We could break this load imbalance by seeking to maximize entropy for this distribution. Our conjecture is that would favor the average case performance rather than the worse case when operating on the "max-entropy transformed" matrix.

For linear system solvers, if we know the matrix \mathbb{M} , and we know the architecture, preconditioning (when affordable) is a better solution. If we run experiments long enough, we choose the best permutation(s) for the architecture, permute \mathbb{M} , and go on testing the next. On one end, preconditioning exerts a full understanding of both the matrix (the problem) and how the final solution will be computed (architecture). On the other end, the simplicity of a random permutation requires no information about the matrix, the vector, and the architecture. Such a simplicity can be exploited directly in Hardware. We are after an understanding when randomization is just enough: We seek to let the hardware do its best with the least effort, or at least with the appearance to be effortless.

Interestingly, this work stems from a sincere surprise about randomization efficacy and its application on custom SpMV. Here, we wish to study this problem systematically so that to help future hardware designs. Intuitively, if we can achieve a uniform distribution of the rows of matrix \mathbb{M} we can have provable expectation of its load balancing across multiple cores. If we have a uniform distribution of accesses on \mathbf{x} we could exploit column load balancing and exploit better sorting algorithms: In practice, the reading of $x_{COL[i]}$ can be reduced to a sorting, and there we know that different sparsity may require different algorithms. This may be a lot to unpack but it translates to a better performance of the sequential algorithm without changing the algorithm or to improved bandwidth utilization.

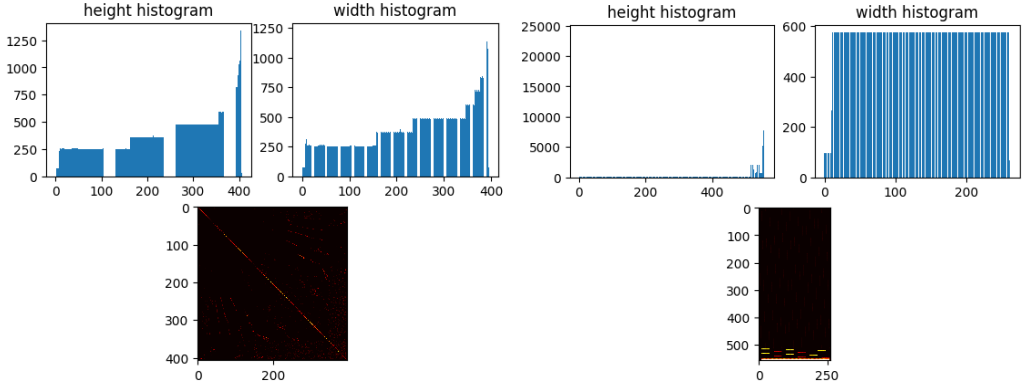


Fig. 1. Left: OPF 3754. Right: LP OSA 07. These are histograms where we represent normalized buckets and counts

We will show that (different) randomness affects architectures and algorithms differently, making randomization a suitable optimization transform especially when the application and hardware are at odds: Hardware (unless programmable) is difficult to change and the matrix sparsity is simple to change. We want to show that there is a randomness hierarchy that we can distinguish as global and local. There are simple-to-find cases where the sparsity breaks randomness optimization. For instance, matrices with dense rows or columns are better partitioned into sparse and dense components and operated on separately.

4 ENTROPY

Patterns in sparse matrices are often visually pleasing, see Figure 1 where we present the height histogram, the width histograms, and a two-dimensional histogram as heat map. We will let someone else using AI picture classification. Intuitively, we would like to express a measure of uniform distribution and here we apply the basics: *Entropy*. Given an histogram $i \in [0, M-1]$ $h_i \in \mathbb{N}$, we define $S = \sum_{i=0}^{M-1} h_i$ and thus we have a probability distribution function $p_i = \frac{h_i}{S}$. The *information* of bin i is defined as $I(i) = -\log_2 p_i$. If we say that the stochastic variable X has PDF p_i then the entropy of X is defined as.

$$H(x) = - \sum_{i=0}^{M-1} p_i \log_2 p_i = \sum_{i=0}^{M-1} p_i I(i) = E[I_x] \quad (1)$$

The maximum entropy is when $\forall i, p_i = p = \frac{1}{M}$; that is, we are observing a uniform distributed event. Our randomization should aim at higher entropy numbers. The entropy for matrix LP OSA 07 is 8.41 and for OPF 3754 is 8.39. We use the entropy specified in the Scipy stats module. A single number is concise and satisfying. If you are pondering why they are so close contrary to their sparsity we discuss this next.

5 UNIFORM DISTRIBUTION

We know that we should **not** compare the entropy numbers of two matrices because entropy does not use any information about the order of the buckets, it uses only their probabilities. By construction, the matrices are quite different in sparsity and in shapes, however their entropy numbers are close. Two matrices with the same number of non-zeros, spaced well enough in the

proper number of bin, will have the same entropy. To appreciate their different sparsity, we should compare their entropy distributions by Jensen-Shannon measure [2] or we could use cumulative distribution function (CDF) measures, which imply an order. Here, we use a representation of a hierarchical 2D-entropy, see Figure 2, where the entropy is split into 2x2, 4x4 and 8x8 (or fewer if the distribution is not square). We have hierarchical entropy heat maps.

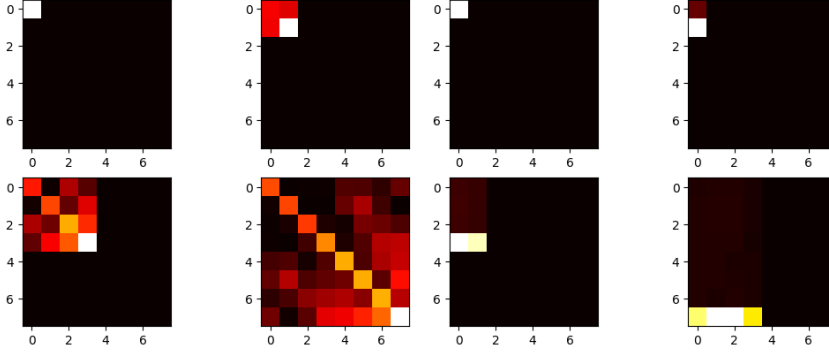


Fig. 2. Hierarchical 2D entropy for OPF 3754 (left) and LP OSA 07 (right).

We can see that even a small 2D-entropy matrix summarizes the nature of the original matrix because it has spatial information. In this work, the entropy matrix is used mostly for visualization purpose more than for comparison purpose. Of course, we can appreciate how the matrix LP OSA 07 has a few very heavy rows and they are clustered. This matrix will help us showing how randomization need some tips. Now we apply row and column random permutation once by row and one by column: Figure 3: OPF has now entropy 11.27 and LP 9.26. The numerical difference is significant. The good news is that for entropy, being an expectation, we can use simple techniques like bootstrap to show that the difference is significant or we have shown that Jensen-Shannon can be used and a significance level is available. What we like to see is the the hierarchical entropy heat map is becoming *more* uniform for at least one of the matrix.

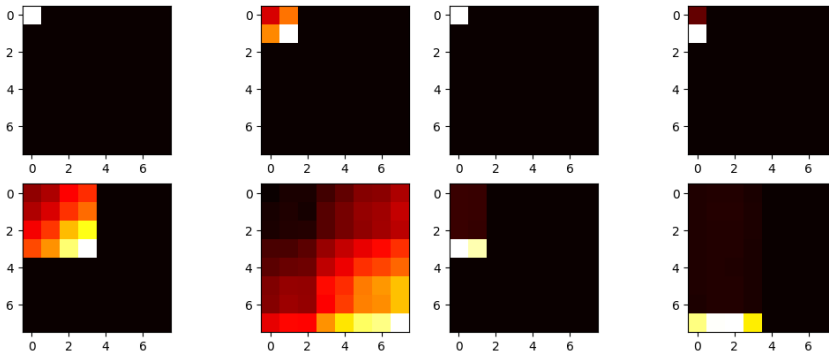


Fig. 3. Hierarchical 2D entropy after row and column random permutation for OPF 3754 (left) and LP OSA 07 (right).

In practice, permutations need some help especially for relatively large matrices. As you can see, the permutation affects locally the matrix. Of course, it depends on the implementation of

the random permutation, we use *numpy* for this. It is reasonable that a slightly modified version of the original is still a random selection and unfortunately they seem too likely in practice. We need to compensate or help the randomization. If we are able to identify the row and column that divide high and low density, we could use them as pivot for a shuffle like in a quick-sort algorithm. We could apply a sorting algorithm but its complexity will be the same of *SpMV*. We use a gradients operations to choose the element with maximum steepness, Figure 4 and 5.

LP achieves entropy 8.67 and 9.58 and OPF achieves 10.47 and 11.40.

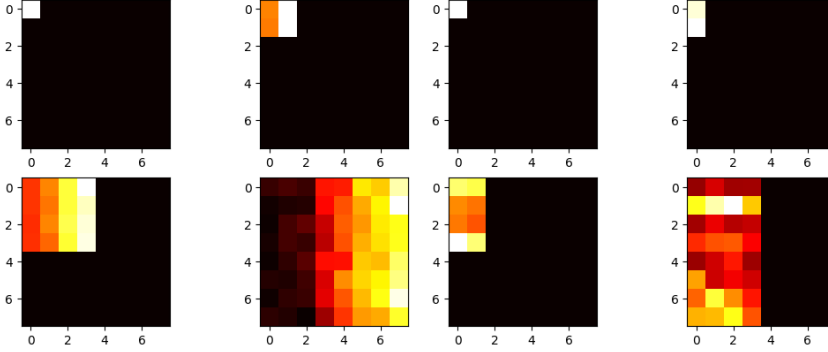


Fig. 4. Hierarchical 2D entropy after height gradient based shuffle and row random permutation for OPF 3754 (left) and LP OSA 07 (right).

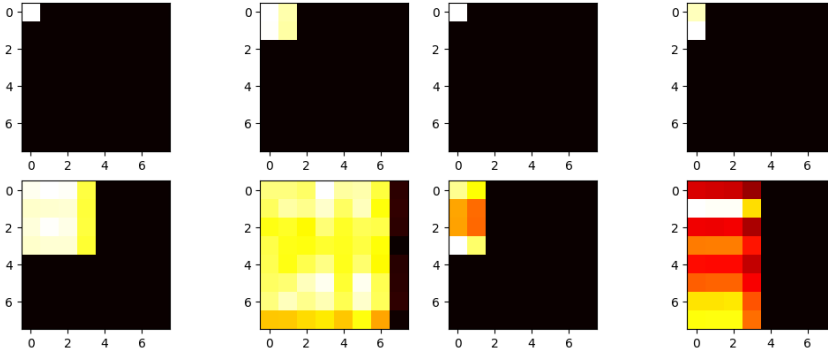


Fig. 5. Hierarchical 2D entropy after height and width gradient shuffle and row and column random permutation for OPF 3754 (left) and LP OSA 07 (right).

If the goal is to achieve a uniformly sparse matrix, it seems that we have the tools to compute and to measure such a sparsity. We admit that we do not try to find the best permutation. But our real goal is to create a work bench where randomization can be tested on different architectures and different algorithms. A randomization with a measurable uniform distribution is preferable than just random. We are interested to find out when random is enough or not enough. Also, consider that to achieve a uniform distribution, we do not need a random transformation and any permutation balancing the number of non-zero is possible, but for now not looked for.

6 MEASURING THE RANDOMIZATION EFFECTS

Whether or not this ever applied to the reader, when we have timed algorithms (i.e., measure execution time), we came to expect variation. The introduction of randomization may hide behind the ever present variance, after all these are algorithms on *small* inputs: small error can be comparable to the overall execution time. Here, we must address this concern even before describing the experiments.

First, we execute every algorithm between 1000 and 5000 times. The time of each experiment is in the seconds, providing a granularity for which we are confident the measuring time error is under control. Thus, for each experiment we provide an average execution time: we measure the time and we divide by the number of trials. Cold starts, the first iteration, are still accounted. To make the measure portable across platform we present GFLOPS, that is, Giga (10^{12}) floating operations per second: $2 * nnz$ divided by the average time in seconds.

Then we repeat the same experiment 32 times. Permutations in *numpy* Python uses a seed that is time sensitive: thus every experiment is independent from the previous. The number 32 is an old statistic trick and it is a minimum number of independent trials to approximate a normal distribution. In practice, they are not but the number is sufficient for most of the cases and it is an excellent starting point.

A short hand legend: **Reg** is the regular matrix without any permutation; **R** stands for random Row permutation; **G-R** stands for gradient-based row shuffle and random row permutation; **G-C** stands for gradient-based column shuffle and random column permutation; **R-C** stands for random row and column permutation. This legend is used in the pictures to be concise, in the tables in the following sections, we use a verbose description. We shall clarify the gradient based approach in the experimental results section 8. Intuitively, we help the random permutation by a quick targeting of high and low volume of the histogram (and thus the matrix).

In Figure 6, we show two plots respectively of the CPU performance using COO and CSR SpMV algorithms for the matrix OPF 3754. The figure represents histograms: The x is GFLOPS and the y label is the number of counts. Thus we show what is the performance distribution of an algorithm. We can see that the CSR algorithms are consistent and the Regular (i.e., the original) has always the best performance. Also the variance of the computation time is small and the shape is approximately Gaussian. Different story for the COO, the permutations introduce long tails, thus $2\times$ performance advantage.

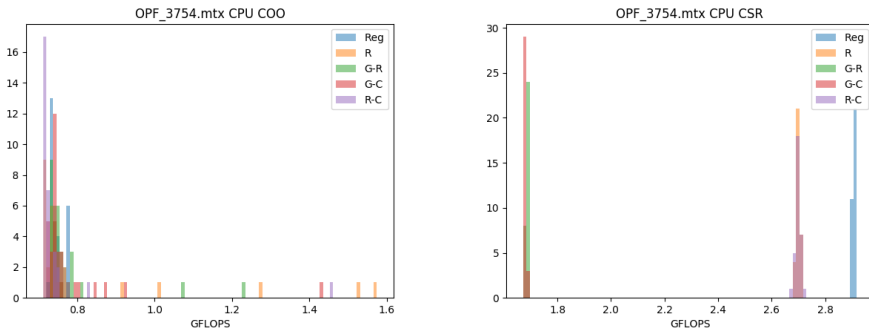


Fig. 6. CPU COO (left) and CPU CSR (left) for OPF 3754

If we take the original matrix and split into parts having the same number of rows, and execute them in parallel using different cores, we can see in Figure 7 that randomization is quite useful.

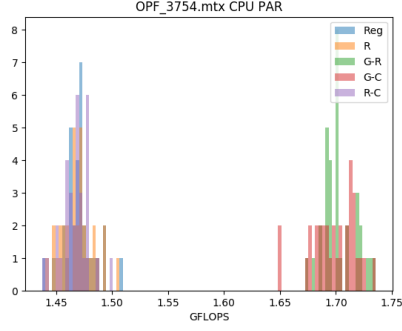


Fig. 7. Parallel CPU CSR for OPF 3754

In Figure 8, 9 and 10, randomization is harmful to the GPU implementation. The OPF 375 matrix is mostly diagonal, thus the vector x is read in close quarters, randomization breaks it. If the load balance is fixed (i.e., by dividing the matrix by row and in equal row), randomization is beneficial.

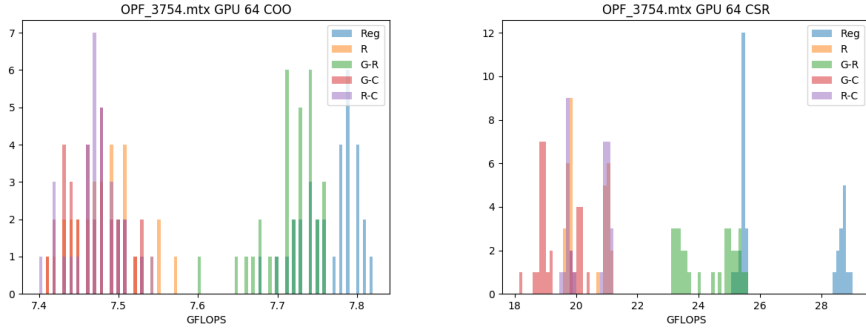


Fig. 8. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

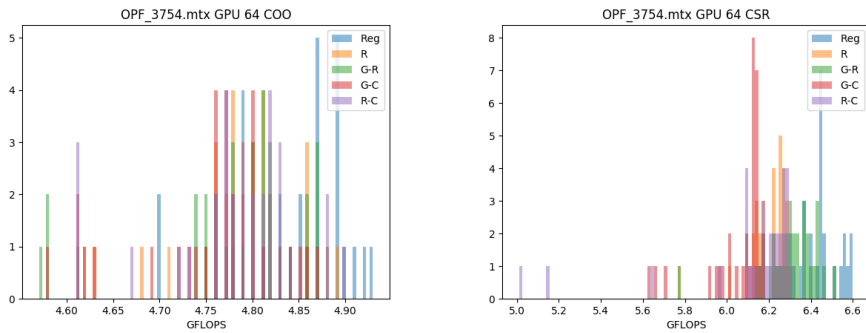


Fig. 9. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

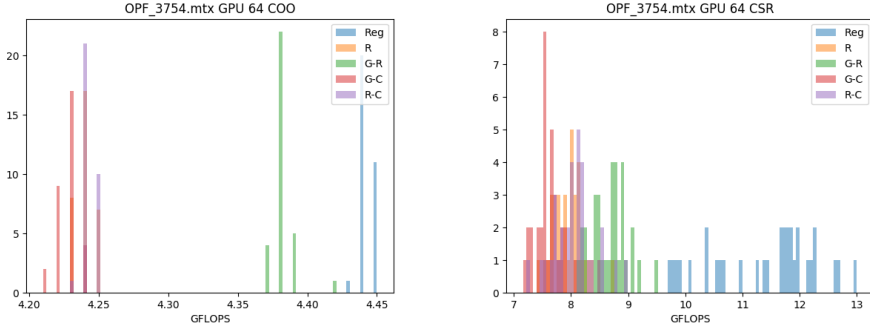


Fig. 10. Fiji, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

For matrix LP OSA 07, randomization helps clearly only for CPU CSR as we show in Figure 11. In Figure 12, 13, and 14, we can see that randomization is harmful but for one GPU, we can show that a single exception is possible (40% improvement).

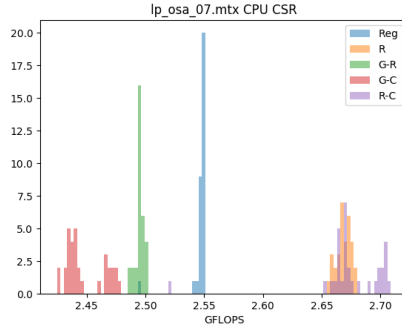


Fig. 11. CPU CSR for LP OSA 07

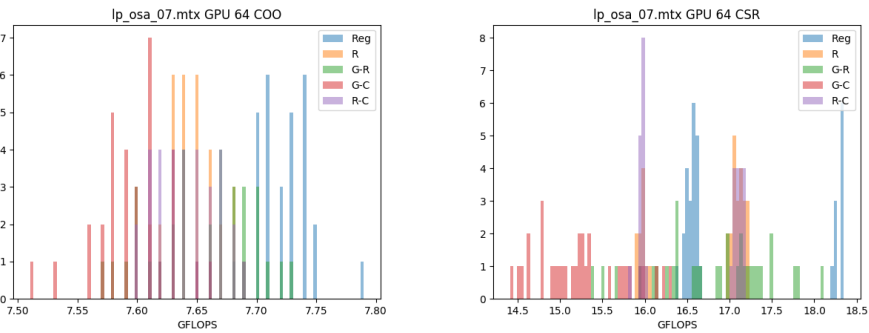


Fig. 12. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

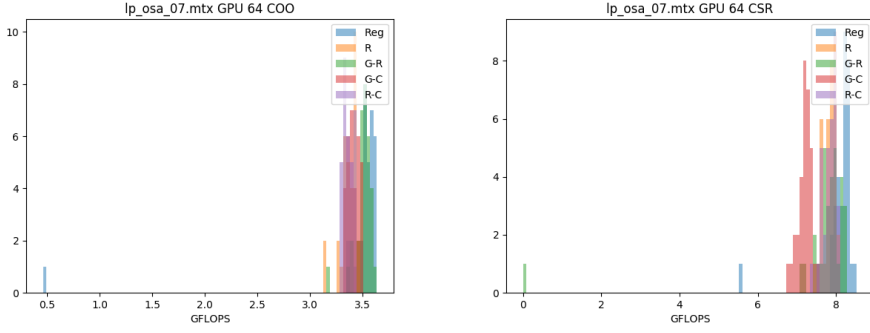


Fig. 13. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

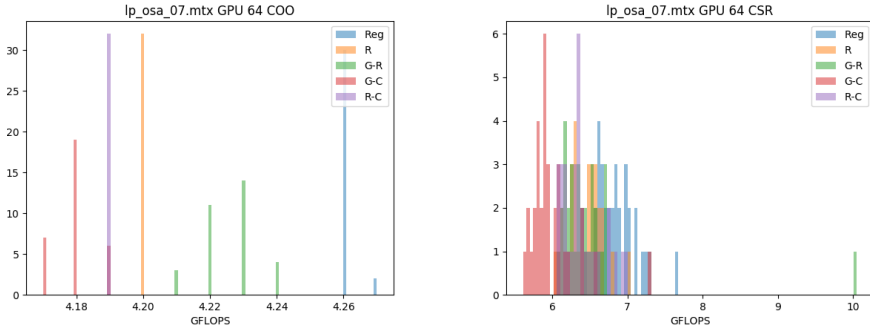


Fig. 14. Fiji, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

An example, the matrix MULT DCOP 01, is where randomization is useful for the CPU, GPU, and the parallel version Figure 15, 16 - 19 and the gains can be up to 10-15%. Consider, we can achieve these improvements without any insights to the architecture, the algorithms and their relationships.

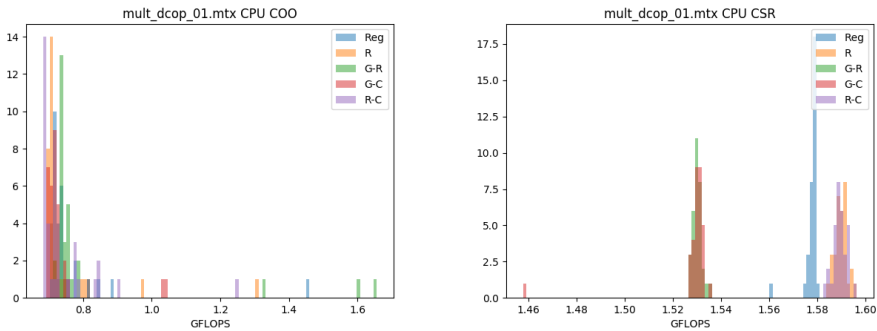


Fig. 15. CPU COO (left) and CPU CSR (right) for MULT DCOP 01

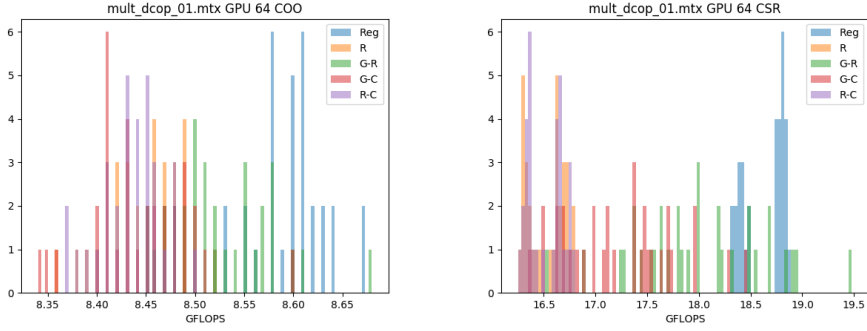


Fig. 16. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

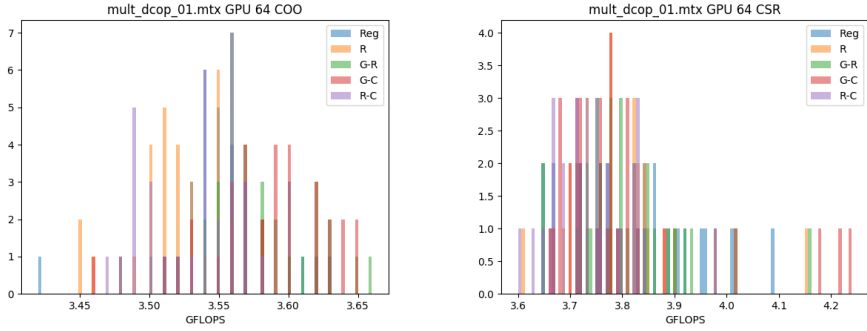


Fig. 17. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

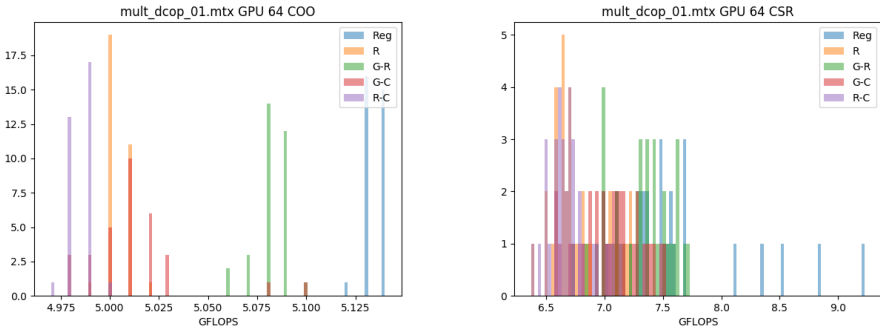


Fig. 18. Fiji, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

What does it mean when randomization does not work? The matrices we use in this work are not chosen randomly (pun not intended), they are the matrices that are difficult to handle in our custom SpMV engines using a combination of sorting networks and systolic arrays. If randomization does not work in our simplified work bench, will not work in our specialized architecture because the reorganization of the matrix or the input and output vector does not have the necessary parallelism,

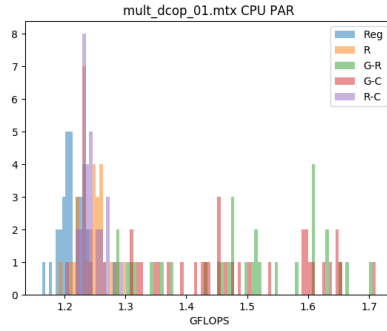


Fig. 19. Parallel CPU CSR for MULT DCOP 01

data locality, and data streaming. We need to do something else. In this case disrupting the memory pattern is not sufficient. Thus, if we cannot beat the pattern, we must exploit it, well not in this work.

7 WORKLOADS

In the previous sections, we defined what we mean for randomization and we present our tools of tricks for the measure of the effects of randomization. Here we describe the work loads, the applications, we use to test the effects of the randomization.

7.1 Python COO and CSR algorithms

The simplicity to compute the SpMV by the code $z = A * b$ in Python is very rewarding. By change of the matrix storage format, $A = A.tocsr()$; $z = A * b$, we have a different algorithm. The performance exploitation is moved to the lower level. The CSR implementation is often two times faster but there are edge cases where the COO and COO with randomization can go beyond and be surprisingly better: MUL DCOP 03 is an example where COO can do well.

Intuitively, Randomization can affect the performance because the basic implementation is a sorting algorithm and it is a fixed algorithm. There are many sorting algorithms and each can be optimal for a different initial distribution. If we knew what is the sorting algorithm we could tailor the input distribution. Here we just play with it.

In Section 8, we present all the results for CPU and GPUS. Keep in mind that these problems are hard, in the sense they do not have fancy performance sheets (these architectures can achieve Tera FLOPs sustained performance for dense computations). If we go through diligently, we can see that there is a 15x performance difference between the single thread CPU and Vega 20 GPU (i.e, 3 vs 40 GFLOPS).

7.2 Parallel CSR using up to 16 cores

Python provides the concept of Pool to exploit a naive parallel computation. We notice that work given to a Pool is split accordingly to the number of elements to separate HW cores. We also noticed that the work load move from a core to another, thus not ideal. Also we notice that Pool introduce a noticeable overhead: a Pool of 1, never achieves the performance of the single thread $z = A * b$. Using Pool allows us to investigate how a naive row partitioning without counting can scale up with number of cores. We tested by splitting the rows to 1–16 cores evenly (one thread per core) and we present the performance for only the best configuration. The randomization goal is to

distribute the work uniformly: a balanced work distribution avoid the unfortunate case where a single core does all the work. We are pleased by the simplicity of the benchmark and we know we can do better.

7.3 GPU COO and CSR algorithms

In this work, we use AMD GPUs and *rocSPARSE* is their current software. The software has a few glitches but overall can be used for different generation of AMD GPUs. We use the COO and CSR algorithms and we provide performance measure for double precision only. The ideas of using different GPUs: it is important to verify that the randomization can be applied independently of the HW. We are not here to compare performance across GPUs and CPUs. Often the limitation is the software, how the software can exploit the hardware or how the software will make easy to use a specific GPU. For example, the Fiji architecture is clearly superior to the Ellesmere, however the latter have better support and the system overall is more stable and user friendly.

The performance of the CSR algorithm is about two times faster than the COO. Most of the algorithms count the number of sparse elements in a row and thus they can decide the work load partition accordingly. Counting give you an edge but without changing the order of the computation there could be cases where the work load is not balanced and a little randomization could help and it does.

7.4 Randomization sometimes works

For the majority of the cases we investigated and reported in the following sections, Randomization does not work. However, there are cases where randomization does work and does work for different algorithms and architectures. If you are in the business of preconditioning, permutations are pretty cheap. If you can find a good one just consider like a preconditioning matrix, which it is.

This shows also that HW has to be more conscious, well the HW designer should, and accept that there are options at software level, at matrix level and beyond.

8 EXPERIMENTAL RESULTS

The main hardware setup is a AMD Threadripper with 16 cores. We have three Radeon GPUs: Vega 20 7nm, Pro 2xFiji, and Pro 2xEllesmere.

Vega 20 can deliver 3.5TFLOPS in double precision and it has 1TB/s HBM memory. Each Fiji provides 0.5 TFLOPS in double precision and has 512GB/s HBM, the card has two chips. The Ellesmere provides 0.3TFLOPS in double precision and has 224GB/s DDR5, the card has two chips. In the performance plots presented earlier and in the following, you will notice that the performance gap between these GPUs is not so marked. We can safely state that *vega* $\sim 2 \times$ *Fiji* and *Fiji* $\sim 2 \times$ *ellesmere*

There are 4 basic randomization formats:

- **Random Row Permutation**, we take the original matrix and permute the rows.
- **Random Row and Column Permutation**, we take the original matrix and permute the rows and the columns.
- **Gradient based row permutation**, we compute the row histogram and we compute the gradient: $h_{i+1} - h_i$. We find a single point where the gradient is maximum, this is the pivot for a shuffle like a magician would shuffle a deck of cards. Then we permute the two parts randomly.
- **Gradient based row and column permutation**, As above but also for the columns.

For large matrices (large number of columns and rows) a permutation tends to be a close variation of the original, still a random permutation. The gradient allows us to describe two areas of the

original matrix where there is a clear and de-marked density variation: for example, there are two uniform distributed sub matrices but one denser than the other. A shuffle redistributes every other sample/card to different parts and these can be permuted locally.

We report in the following the performance results GFLOPS, we introduce a * following the best performance. This is tedious to read and, we assure, to write. The code and the results are available as software repository. Remember each experiment is based on 32 different runs and thus we report maximum, minimum, and mean as a summary. We use the symbol H for entropy.

9 VEGA VII AND THREADRIPPER

mult_dcop_03.mtx

Regular

CPU COO	min	0.728	max	0.880	mean	0.757	
CPU CSR	min	1.563	max	1.581	mean	1.577	
GPU 64 COO	min	8.540	max	8.670	mean	8.619	
	CSR	min	18.320	max	18.930	mean	18.620
CPU PAR	min	1.170	max	1.269	mean	1.226	
H	min	9.689	max	9.689	mean	9.689	

Row-Premute

CPU COO	min	0.710	max	0.845	mean	0.724	
CPU CSR	min	1.549	max	1.597	mean	1.589	
GPU 64 COO	min	8.360	max	8.540	mean	8.442	
	CSR	min	16.260	max	16.780	mean	16.551
CPU PAR	min	1.205	max	1.319	mean	1.263	
H	min	10.737	max	10.742	mean	10.740	

Row-Gradient

CPU COO	min	0.706	max	1.603	mean	0.806	
CPU CSR	min	1.493	max	1.534	mean	1.528	
GPU 64 COO	min	8.430	max	8.610	mean	8.527	
	CSR	min	17.070	max	18.970	mean	18.115
CPU PAR	min	1.331	max	1.695	mean	1.513	
H	min	10.576	max	10.585	mean	10.580	

Column-Gradient

CPU COO	min	0.694	max	1.632	mean	0.797	
CPU CSR	min	1.491	max	1.534	mean	1.529	
GPU 64 COO	min	8.350	max	8.520	mean	8.429	
	CSR	min	15.970	max	18.180	mean	17.124
CPU PAR	min	1.321	max	1.728	mean	1.514	
H	min	10.826	max	10.840	mean	10.833	

Row-Column-Permute

CPU COO	min	0.688	max	0.757	mean	0.696	
CPU CSR	min	1.490	max	1.595	mean	1.584	
GPU 64 COO	min	8.380	max	8.500	mean	8.445	
	CSR	min	16.230	max	16.780	mean	16.513
CPU PAR	min	1.192	max	1.274	mean	1.237	
H	min	10.737	max	10.742	mean	10.740	

mult_dcop_01.mtx

Regular

CPU COO	min	0.710	max	1.453	mean	0.761	
CPU CSR	min	1.561	max	1.581	mean	1.578	
GPU 64 COO	min	8.520	max	8.670	mean	8.597	
	CSR	min	18.320	max	18.870	mean	18.636
CPU PAR	min	1.163	max	1.246	mean	1.212	
H	min	9.689	max	9.689	mean	9.689	

Row-Premute

CPU COO	min	0.699	max	1.305	mean	0.745	
CPU CSR	min	1.585	max	1.597	mean	1.590	
GPU 64 COO	min	8.360	max	8.520	mean	8.446	
	CSR	min	16.260	max	16.780	mean	16.528
CPU PAR	min	1.192	max	1.298	mean	1.242	
H	min	10.738	max	10.742	mean	10.740	

Row-Gradient

CPU COO	min	0.709	max	1.656	mean	0.819	
CPU CSR	min	1.527	max	1.535	mean	1.530	
GPU 64 COO	min	8.450	max	8.680	mean	8.527	
	CSR	min	16.520	max	19.480	mean	17.984
CPU PAR	min	1.280	max	1.704	mean	1.485	
H	min	10.572	max	10.585	mean	10.581	

Column-Gradient

CPU COO	min	0.698	max	1.042	mean	0.737	
CPU CSR	min	1.458	max	1.536	mean	1.528	
GPU 64 COO	min	8.340	max	8.600	mean	8.443	
	CSR	min	16.360	max	18.450	mean	17.247
CPU PAR	min	1.307	max	1.712	mean	1.494	
H	min	10.823	max	10.841	mean	10.835	

Row-Column-Permute

CPU COO	min	0.683	max	1.247	mean	0.749	
CPU CSR	min	1.583	max	1.595	mean	1.590	
GPU 64 COO	min	8.370	max	8.500	mean	8.435	
	CSR	min	16.250	max	16.780	mean	16.518
CPU PAR	min	1.206	max	1.291	mean	1.243	
H	min	10.738	max	10.742	mean	10.740	

mult_dcop_02.mtx

Regular

CPU COO	min	1.615	max	1.677	mean	1.652	
CPU CSR	min	1.539	max	1.579	mean	1.575	
GPU 64 COO	min	8.530	max	8.700	mean	8.614	
	CSR	min	18.290	max	18.890	mean	18.597
CPU PAR	min	1.120	max	1.248	mean	1.211	
H	min	9.689	max	9.689	mean	9.689	

Row-Premute

CPU COO	min	0.684	max	0.780	mean	0.705	
CPU CSR	min	1.558	max	1.596	mean	1.588	
GPU 64 COO	min	8.360	max	8.490	mean	8.433	
	CSR	min	16.240	max	16.750	mean	16.552
CPU PAR	min	1.182	max	1.277	mean	1.242	
H	min	10.737	max	10.742	mean	10.740	

Row-Gradient

CPU COO	min	0.704	max	1.373	mean	0.790	
CPU CSR	min	1.518	max	1.535	mean	1.529	
GPU 64 COO	min	8.420	max	8.590	mean	8.517	
	CSR	min	16.680	max	19.550	mean	17.907
CPU PAR	min	1.328	max	1.713	mean	1.484	
H	min	10.572	max	10.585	mean	10.581	

Column-Gradient

CPU COO	min	0.697	max	1.460	mean	0.742	
CPU CSR	min	1.517	max	1.534	mean	1.527	
GPU 64 COO	min	8.330	max	8.490	mean	8.420	
	CSR	min	16.020	max	18.390	mean	17.303
CPU PAR	min	1.321	max	1.709	mean	1.557	
H	min	10.823	max	10.843	mean	10.835	

Row-Column-Permute

CPU COO	min	0.691	max	0.746	mean	0.698	
CPU CSR	min	1.568	max	1.595	mean	1.587	
GPU 64 COO	min	8.350	max	8.500	mean	8.436	
	CSR	min	16.250	max	16.780	mean	16.517
CPU PAR	min	1.187	max	1.280	mean	1.228	
H	min	10.739	max	10.743	mean	10.740	

lp_fit2d.mtx

Regular

CPU COO	min	0.774	max	0.804	mean	0.793	
CPU CSR	min	2.538	max	2.550	mean	2.547	
GPU 64 COO	min	7.060	max	7.170	mean	7.101	
	CSR	min	15.650	max	18.700	mean	18.031
CPU PAR	min	1.537	max	1.645	mean	1.590	
H	min	11.109	max	11.109	mean	11.109	

Row-Premute

CPU COO	min	0.740	max	0.776	mean	0.746	
CPU CSR	min	3.302	max	3.328	mean	3.317	
GPU 64 COO	min	7.040	max	7.180	mean	7.098	
	CSR	min	15.690	max	18.580	mean	16.732
CPU PAR	min	1.327	max	1.482	mean	1.422	
H	min	11.098	max	11.105	mean	11.101	

Row-Gradient

CPU COO	min	0.739	max	2.092	mean	1.091	
CPU CSR	min	2.539	max	2.546	mean	2.543	
GPU 64 COO	min	7.040	max	7.150	mean	7.100	
	CSR	min	15.520	max	18.560	mean	17.547
CPU PAR	min	1.401	max	1.661	mean	1.525	
H	min	11.109	max	11.109	mean	11.109	

Column-Gradient

CPU COO	min	0.726	max	2.065	mean	1.011	
CPU CSR	min	2.539	max	2.550	mean	2.546	
GPU 64 COO	min	6.800	max	7.140	mean	7.080	
	CSR	min	15.480	max	18.560	mean	16.866
CPU PAR	min	1.391	max	1.737	mean	1.563	
H	min	11.329	max	11.333	mean	11.331	

Row-Column-Permute

CPU COO	min	0.746	max	0.782	mean	0.754	
CPU CSR	min	3.310	max	3.324	mean	3.318	
GPU 64 COO	min	7.030	max	7.160	mean	7.100	
	CSR	min	15.730	max	18.530	mean	17.362
CPU PAR	min	1.340	max	1.451	mean	1.401	
H	min	11.099	max	11.104	mean	11.102	

bloweya.mtx

Regular

CPU COO	min	0.727	max	1.815	mean	0.892	
CPU CSR	min	2.867	max	2.936	mean	2.917	
GPU 64 COO	min	0.000	max	0.000	mean	0.000	
	CSR	min	0.000	max	0.000	mean	0.000
CPU PAR	min	1.680	max	1.751	mean	1.719	
H	min	7.205	max	7.205	mean	7.205	

Row-Premute

CPU COO	min	0.678	max	1.483	mean	0.746	
CPU CSR	min	2.311	max	2.326	mean	2.320	
GPU 64 COO	min	6.840	max	7.270	mean	6.930	
	CSR	min	15.650	max	16.800	mean	16.233
CPU PAR	min	1.649	max	1.730	mean	1.682	
H	min	11.026	max	11.031	mean	11.029	

Row-Gradient

CPU COO	min	0.708	max	1.209	mean	0.779
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Column-Gradient	CPU CSR	min	1.648	max	1.735	mean	1.709	Row-Column-Permute	CSR	min	24.340	max	26.140	mean	25.393
	GPU 64 COO	min	6.920	max	7.080	mean	7.015		CPU PAR	min	2.184	max	2.272	mean	2.223
	CSR	min	16.950	max	19.500	mean	17.794		H	min	11.873	max	11.882	mean	11.878
	CPU PAR	min	1.497	max	1.743	mean	1.608		CPU COO	min	0.707	max	0.748	mean	0.714
	H	min	10.298	max	10.304	mean	10.301		CPU CSR	min	2.458	max	2.511	mean	2.506
	CPU COO	min	0.709	max	1.536	mean	0.817		GPU 64 COO	min	10.880	max	11.070	mean	10.957
	CPU CSR	min	1.705	max	1.753	mean	1.735		CSR	min	24.890	max	26.490	mean	25.642
	GPU 64 COO	min	6.800	max	7.120	mean	6.865		CPU PAR	min	2.209	max	2.282	mean	2.240
	CSR	min	15.480	max	17.710	mean	16.470		H	min	11.834	max	11.840	mean	11.838
	CPU PAR	min	1.446	max	1.718	mean	1.591		brainpc2.mtx Regular	CPU COO	min	0.732	max	0.751	mean
H	min	10.880	max	10.886	mean	10.883	CPU CSR	min		2.885	max	2.916	mean	2.909	
CPU COO	min	0.670	max	1.024	mean	0.706	GPU 64 COO	min		0.000	max	0.000	mean	0.000	
CPU CSR	min	2.199	max	2.340	mean	2.326	CSR	min		0.000	max	0.000	mean	0.000	
GPU 64 COO	min	6.880	max	6.980	mean	6.933	CPU PAR	min		1.276	max	1.299	mean	1.286	
CSR	min	15.610	max	16.900	mean	16.227	H	min		7.478	max	7.478	mean	7.478	
CPU PAR	min	1.598	max	1.668	mean	1.632	Row-Premute	CPU COO		min	0.727	max	0.855	mean	0.736
H	min	11.025	max	11.032	mean	11.029		CPU CSR		min	2.385	max	2.411	mean	2.397
CPU COO	min	0.715	max	1.798	mean	0.885		GPU 64 COO		min	8.120	max	8.410	mean	8.206
CPU CSR	min	2.495	max	2.551	mean	2.547		CSR		min	18.670	max	19.960	mean	19.536
GPU 64 COO	min	7.650	max	7.790	mean	7.718		CPU PAR	min	1.293	max	1.340	mean	1.314	
CSR	min	16.390	max	18.350	mean	17.093		H	min	9.809	max	9.813	mean	9.811	
CPU PAR	min	0.963	max	1.012	mean	0.995		Row-Gradient	CPU COO	min	0.696	max	1.546	mean	0.785
H	min	8.412	max	8.412	mean	8.412			CPU CSR	min	1.361	max	1.420	mean	1.411
CPU COO	min	0.720	max	2.078	mean	1.104			GPU 64 COO	min	8.190	max	8.550	mean	8.302
CPU CSR	min	2.656	max	2.679	mean	2.669			CSR	min	18.700	max	21.000	mean	19.890
GPU 64 COO	min	7.610	max	7.690	mean	7.647	CPU PAR		min	1.435	max	1.666	mean	1.549	
CSR	min	15.910	max	17.210	mean	16.750	H		min	9.721	max	9.727	mean	9.723	
CPU PAR	min	0.890	max	0.940	mean	0.918	Column-Gradient		CPU COO	min	0.698	max	1.467	mean	0.746
H	min	9.255	max	9.258	mean	9.256			CPU CSR	min	1.377	max	1.423	mean	1.414
CPU COO	min	0.725	max	2.078	mean	1.041			GPU 64 COO	min	8.110	max	8.290	mean	8.187
CPU CSR	min	2.487	max	2.502	mean	2.495			CSR	min	18.090	max	20.190	mean	19.217
GPU 64 COO	min	7.570	max	7.730	mean	7.655		CPU PAR	min	1.345	max	1.681	mean	1.518	
CSR	min	15.370	max	18.100	mean	16.803		H	min	10.369	max	10.372	mean	10.370	
CPU PAR	min	1.435	max	1.796	mean	1.592		Row-Column-Permute	CPU COO	min	0.698	max	1.390	mean	0.788
H	min	8.637	max	8.678	mean	8.672			CPU CSR	min	2.387	max	2.410	mean	2.399
CPU COO	min	0.724	max	1.990	mean	1.000			GPU 64 COO	min	8.120	max	8.260	mean	8.191
CPU CSR	min	2.425	max	2.477	mean	2.448			CSR	min	18.530	max	19.960	mean	19.307
GPU 64 COO	min	7.510	max	7.660	mean	7.596	CPU PAR		min	1.295	max	1.347	mean	1.319	
CSR	min	14.410	max	16.290	mean	15.267	H		min	9.809	max	9.813	mean	9.811	
CPU PAR	min	1.238	max	1.774	mean	1.534	shermanACb.mtx Regular		CPU COO	min	0.712	max	1.201	mean	0.756
H	min	9.447	max	9.603	mean	9.576			CPU CSR	min	1.558	max	1.601	mean	1.596
CPU COO	min	0.738	max	1.950	mean	1.071			GPU 64 COO	min	7.080	max	7.370	mean	7.184
CPU CSR	min	2.522	max	2.709	mean	2.675			CSR	min	17.580	max	19.480	mean	18.770
GPU 64 COO	min	7.600	max	7.690	mean	7.641		CPU PAR	min	1.286	max	1.511	mean	1.447	
CSR	min	15.820	max	17.190	mean	16.572		H	min	8.600	max	8.600	mean	8.600	
CPU PAR	min	0.891	max	0.944	mean	0.924		Row-Premute	CPU COO	min	0.689	max	0.890	mean	0.704
H	min	9.255	max	9.258	mean	9.256			CPU CSR	min	1.600	max	1.630	mean	1.618
CPU COO	min	0.732	max	1.837	mean	1.076			GPU 64 COO	min	7.000	max	7.180	mean	7.061
CPU CSR	min	2.563	max	2.586	mean	2.577			CSR	min	15.760	max	17.240	mean	16.625
GPU 64 COO	min	11.340	max	11.860	mean	11.441	CPU PAR		min	1.296	max	1.419	mean	1.365	
CSR	min	36.010	max	40.960	mean	38.048	H		min	10.376	max	10.380	mean	10.379	
CPU PAR	min	2.019	max	2.204	mean	2.130	Row-Gradient		CPU COO	min	0.704	max	1.615	mean	0.806
H	min	8.228	max	8.228	mean	8.228			CPU CSR	min	1.355	max	1.370	mean	1.362
CPU COO	min	0.718	max	0.751	mean	0.732			GPU 64 COO	min	7.020	max	7.160	mean	7.083
CPU CSR	min	2.488	max	2.507	mean	2.498			CSR	min	0.000	max	16.290	mean	15.076
GPU 64 COO	min	10.810	max	11.090	mean	10.949		CPU PAR	min	1.256	max	1.520	mean	1.405	
CSR	min	24.860	max	26.410	mean	25.527		H	min	9.915	max	9.925	mean	9.921	
CPU PAR	min	1.978	max	2.290	mean	2.135		Column-Gradient	CPU COO	min	0.702	max	1.626	mean	0.844
H	min	11.836	max	11.840	mean	11.838			CPU CSR	min	1.327	max	1.374	mean	1.364
CPU COO	min	0.722	max	1.794	mean	0.769			GPU 64 COO	min	6.920	max	7.210	mean	7.030
CPU CSR	min	2.407	max	2.421	mean	2.416			CSR	min	0.000	max	15.260	mean	14.279
GPU 64 COO	min	11.210	max	11.480	mean	11.317	CPU PAR		min	1.283	max	1.531	mean	1.385	
CSR	min	31.920	max	34.690	mean	33.246	H		min	10.572	max	10.595	mean	10.590	
CPU PAR	min	2.184	max	2.302	mean	2.232	Row-Column-Permute		CPU COO	min	0.707	max	1.532	mean	0.924
H	min	10.742	max	10.757	mean	10.748			CPU CSR	min	1.606	max	1.634	mean	1.624
CPU COO	min	0.720	max	0.916	mean	0.742			GPU 64 COO	min	6.970	max	7.110	mean	7.045
CPU CSR	min	2.395	max	2.410	mean	2.402			CSR	min	15.850	max	17.310	mean	16.783
GPU 64 COO	min	10.840	max	11.070	mean	10.946		CPU PAR	min	1.286	max	1.406	mean	1.357	
CPU PAR	min	1.286	max	1.406	mean	1.357									
CPU COO	min	0.707	max	1.532	mean	0.924									
CPU CSR	min	1.606	max	1.634	mean	1.624									
GPU 64 COO	min	6.970	max	7.110	mean	7.045									
CSR	min	15.850	max	17.310	mean	16.783									
CPU PAR	min	1.286	max	1.406	mean	1.357									

cvxqp3.mtx Regular	H min 10.377 max 10.382 mean 10.379				Row-Premute	CPU COO min 0.733 max 1.640 mean 0.777			
						CPU CSR min 2.450 max 2.543 mean 2.525			
						GPU 64 COO min 7.200 max 7.320 mean 7.268			
						CSR min 17.420 max 18.540 mean 18.102			
						CPU PAR min 1.474 max 1.595 mean 1.546			
						H min 10.042 max 10.046 mean 10.044			
					Row-Gradient				
						CPU COO min 0.712 max 0.926 mean 0.750			
						CPU CSR min 1.819 max 1.846 mean 1.832			
						GPU 64 COO min 7.210 max* 7.370 mean 7.298			
Row-Premute						CSR min 17.550 max*20.740 mean 19.089			
						CPU PAR min 1.256 max 1.554 mean 1.495			
						H min 9.666 max 9.704 mean 9.690			
					Column-Gradient				
						CPU COO min 0.710 max* 1.690 mean 0.791			
						CPU CSR min 1.813 max 1.836 mean 1.830			
						GPU 64 COO min 7.130 max 7.310 mean 7.211			
						CSR min 16.550 max 18.690 mean 17.617			
						CPU PAR min 1.385 max 1.539 mean 1.506			
						H min 10.611 max*10.659 mean 10.634			
Row-Gradient					Row-Column-Permute				
						CPU COO min 0.709 max 1.531 mean 0.963			
						CPU CSR min 2.506 max 2.648 mean 2.622			
						GPU 64 COO min 7.140 max 7.330 mean 7.244			
						CSR min 17.410 max 18.520 mean 18.148			
						CPU PAR min 1.466 max 1.574 mean 1.528			
						H min 10.041 max 10.046 mean 10.044			
					OPF_6000.mtx Regular				
						CPU COO min 0.714 max 0.731 mean 0.720			
						CPU CSR min 2.667 max* 2.770 mean 2.720			
Column-Gradient						GPU 64 COO min 12.310 max*12.550 mean 12.425			
						CSR min 39.860 max*43.770 mean 42.075			
						CPU PAR min 1.735 max 1.945 mean 1.845			
						H min 8.799 max 8.799 mean 8.799			
					Row-Premute				
						CPU COO min 0.689 max 0.710 mean 0.695			
						CPU CSR min 2.358 max 2.413 mean 2.392			
						GPU 64 COO min 11.430 max 11.770 mean 11.549			
						CSR min 24.470 max 25.580 mean 24.785			
						CPU PAR min 1.758 max 1.896 mean 1.829			
						H min 11.872 max 11.877 mean 11.875			
Row-Premute					Row-Gradient				
						CPU COO min 0.716 max 0.775 mean 0.739			
						CPU CSR min 1.651 max 1.689 mean 1.675			
						GPU 64 COO min 12.100 max 12.410 mean 12.205			
						CSR min 31.670 max 34.910 mean 33.370			
						CPU PAR min 2.079 max* 2.286 mean 2.207			
						H min 11.111 max 11.116 mean 11.113			
					Column-Gradient				
						CPU COO min 0.715 max* 1.021 mean 0.743			
						CPU CSR min 1.655 max 1.674 mean 1.666			
Row-Gradient						GPU 64 COO min 11.340 max 11.560 mean 11.463			
						CSR min 23.770 max 25.470 mean 24.489			
						CPU PAR min 2.056 max 2.172 mean 2.118			
						H min 12.040 max*12.047 mean 12.043			
					Row-Column-Permute				
						CPU COO min 0.677 max 0.785 mean 0.687			
						CPU CSR min 2.325 max 2.434 mean 2.369			
						GPU 64 COO min 11.450 max 11.650 mean 11.538			
						CSR min 24.330 max 25.560 mean 25.008			
						CPU PAR min 1.631 max 1.776 mean 1.709			
						H min 11.873 max 11.877 mean 11.875			
Column-Gradient					OPF_3754.mtx Regular				
						CPU COO min 0.726 max 0.774 mean 0.747			
						CPU CSR min 2.898 max* 2.919 mean 2.908			
						GPU 64 COO min 7.680 max* 7.820 mean 7.766			
						CSR min 25.070 max*29.030 mean 26.756			
						CPU PAR min 1.437 max 1.508 mean 1.471			
						H min 8.393 max 8.393 mean 8.393			
					Row-Premute				
						CPU COO min 0.714 max* 1.574 mean 0.817			
						CPU CSR min 2.686 max 2.711 mean 2.699			
Row-Premute						GPU 64 COO min 7.410 max 7.570 mean 7.484			
						CSR min 19.600 max 21.190 mean 20.307			
						CPU PAR min 1.443 max 1.505 mean 1.469			
						H min 11.267 max 11.272 mean 11.269			
					Row-Gradient				
						CPU COO min 0.723 max 1.232 mean 0.775			
TSOPF_FS_b9_c6.mtx Regular									

Column-Gradient	CPU CSR	min	1.672	max	1.691	mean	1.685	Row-Column-Permute	CSR	min	15.680	max	17.870	mean	16.540
	GPU 64 COO	min	7.600	max	7.760	mean	7.716		CPU PAR	min	1.429	max	1.488	mean	1.468
	CSR	min	23.160	max	25.590	mean	24.304		H	min	10.931	max	10.945	mean	10.938
	CPU PAR	min	1.675	max*	1.736	mean	1.703		CPU COO	min	0.728	max	1.646	mean	1.037
	H	min	10.463	max	10.472	mean	10.468		CPU CSR	min	2.472	max	2.488	mean	2.480
	CPU COO	min	0.726	max	1.431	mean	0.778		GPU 64 COO	min	5.410	max	5.480	mean	5.449
	CPU CSR	min	1.671	max	1.685	mean	1.679		CSR	min	15.760	max	17.560	mean	16.654
	GPU 64 COO	min	7.410	max	7.530	mean	7.467		CPU PAR	min	1.428	max	1.513	mean	1.474
	CSR	min	18.140	max	20.350	mean	19.315		H	min	10.959	max*	10.967	mean	10.963
	CPU PAR	min	1.650	max	1.736	mean	1.699		gen4.mtx Regular						
H	min	11.393	max*	11.401	mean	11.397	CPU COO	min		0.737	max	1.977	mean	1.431	
Row-Column-Permute	CPU COO	min	0.711	max	1.458	mean	0.751	CPU CSR		min	2.674	max	2.688	mean	2.681
	CPU CSR	min	2.678	max	2.717	mean	2.700	GPU 64 COO		min	5.900	max	6.000	mean	5.954
	GPU 64 COO	min	7.400	max	7.540	mean	7.471	CSR		min	13.650	max	15.410	mean	14.657
	CSR	min	19.560	max	21.150	mean	20.453	CPU PAR		min	1.468	max	1.521	mean	1.491
	CPU PAR	min	1.440	max	1.499	mean	1.467	H		min	9.234	max	9.234	mean	9.234
	H	min	11.266	max	11.272	mean	11.269	CPU COO		min	0.740	max*	2.048	mean	1.121
	CPU COO	min	0.754	max*	1.829	mean	1.204	CPU CSR		min	2.777	max	2.798	mean	2.790
	CPU CSR	min	2.610	max*	2.624	mean	2.618	GPU 64 COO		min	5.910	max	5.970	mean	5.944
	GPU 64 COO	min	9.530	max*	9.870	mean	9.640	CSR	min	13.700	max	15.370	mean	14.541	
	CSR	min	23.990	max*	25.910	mean	24.992	CPU PAR	min	1.468	max	1.546	mean	1.502	
Row-Premute	CPU PAR	min	1.311	max	1.380	mean	1.357	H	min	10.250	max	10.255	mean	10.252	
	H	min	8.364	max	8.364	mean	8.364	CPU COO	min	0.740	max	1.790	mean	0.994	
	CPU COO	min	0.740	max	0.885	mean	0.755	CPU CSR	min	2.663	max	2.682	mean	2.674	
	CPU CSR	min	2.574	max	2.611	mean	2.597	GPU 64 COO	min	5.890	max*	6.160	mean	5.946	
	GPU 64 COO	min	9.320	max	9.510	mean	9.397	CSR	min	13.780	max*	17.520	mean	15.601	
	CSR	min	19.960	max	21.190	mean	20.696	CPU PAR	min	1.479	max*	1.619	mean	1.569	
	CPU PAR	min	1.303	max	1.371	mean	1.345	H	min	9.939	max	9.955	mean	9.948	
	H	min	10.059	max	10.062	mean	10.061	CPU COO	min	0.743	max	1.991	mean	0.981	
	CPU COO	min	0.723	max	0.984	mean	0.753	CPU CSR	min	2.620	max	2.654	mean	2.646	
	CPU CSR	min	1.781	max	1.809	mean	1.803	GPU 64 COO	min	5.840	max	5.910	mean	5.885	
Column-Gradient	GPU 64 COO	min	9.380	max	9.660	mean	9.464	CSR	min	13.130	max	17.040	mean	15.008	
	CSR	min	15.770	max	19.090	mean	18.037	CPU PAR	min	1.477	max	1.607	mean	1.559	
	CPU PAR	min	1.775	max*	1.924	mean	1.868	H	min	10.858	max*	10.876	mean	10.864	
	H	min	10.205	max	10.233	mean	10.219	CPU COO	min	0.742	max	2.010	mean	1.124	
	CPU COO	min	0.715	max	0.926	mean	0.757	CPU CSR	min	2.789	max*	2.800	mean	2.795	
	CPU CSR	min	1.729	max	1.802	mean	1.791	GPU 64 COO	min	5.900	max	5.980	mean	5.941	
	GPU 64 COO	min	9.080	max	9.270	mean	9.158	CSR	min	13.640	max	15.410	mean	14.556	
	CSR	min	13.980	max	15.780	mean	14.938	CPU PAR	min	1.462	max	1.540	mean	1.504	
	CPU PAR	min	1.751	max	1.906	mean	1.846	H	min	10.250	max	10.253	mean	10.252	
	H	min	11.213	max*	11.232	mean	11.222	Maragall_6.mtx Regular	CPU COO	min	0.725	max	0.741	mean	0.729
Row-Column-Permute	CPU COO	min	0.732	max	1.598	mean	0.785		CPU CSR	min	2.345	max	2.409	mean	2.372
	CPU CSR	min	2.594	max	2.602	mean	2.599		GPU 64 COO	min	18.200	max	18.770	mean	18.357
	GPU 64 COO	min	9.340	max	9.460	mean	9.394		CSR	min	38.310	max*	40.240	mean	39.477
	CSR	min	19.950	max	21.500	mean	20.544		CPU PAR	min	0.789	max	0.813	mean	0.797
	CPU PAR	min	1.326	max	1.374	mean	1.354		H	min	9.930	max	9.930	mean	9.930
	H	min	10.059	max	10.062	mean	10.061		CPU COO	min	0.709	max	0.779	mean	0.715
	CPU COO	min	0.759	max	0.795	mean	0.780		CPU CSR	min	2.675	max	2.715	mean	2.696
	CPU CSR	min	2.479	max*	2.565	mean	2.557		GPU 64 COO	min	17.810	max	18.030	mean	17.935
	GPU 64 COO	min	5.490	max*	5.650	mean	5.552		CSR	min	29.650	max	30.580	mean	30.109
	CSR	min	16.700	max	19.460	mean	18.004	CPU PAR	min	0.857	max	0.940	mean	0.904	
Row-Premute	CPU PAR	min	1.456	max*	1.523	mean	1.492	H	min	10.777	max	10.779	mean	10.778	
	H	min	7.132	max	7.132	mean	7.132	CPU COO	min	0.710	max*	1.566	mean	0.755	
	CPU COO	min	0.695	max	0.943	mean	0.726	CPU CSR	min	2.042	max	2.159	mean	2.120	
	CPU CSR	min	2.480	max	2.488	mean	2.485	GPU 64 COO	min	18.460	max*	18.960	mean	18.665	
	GPU 64 COO	min	5.410	max	5.490	mean	5.453	CSR	min	25.650	max	27.330	mean	26.549	
	CSR	min	15.700	max	17.520	mean	16.678	CPU PAR	min	2.257	max	2.612	mean	2.416	
	CPU PAR	min	1.422	max	1.514	mean	1.474	H	min	11.251	max	11.301	mean	11.285	
	H	min	10.959	max	10.966	mean	10.963	CPU COO	min	0.711	max	0.743	mean	0.725	
	CPU COO	min	0.723	max*	2.029	mean	0.990	CPU CSR	min	2.036	max	2.161	mean	2.110	
	CPU CSR	min	2.411	max	2.427	mean	2.421	GPU 64 COO	min	17.840	max	18.860	mean	18.149	
Row-Gradient	GPU 64 COO	min	5.490	max	5.560	mean	5.534	CSR	min	19.410	max	20.690	mean	20.066	
	CSR	min	16.350	max*	19.560	mean	17.784	CPU PAR	min	2.174	max*	2.546	mean	2.349	
	CPU PAR	min	1.441	max	1.509	mean	1.477	H	min	12.011	max*	12.072	mean	12.052	
	H	min	9.512	max	9.526	mean	9.520	CPU COO	min	0.712	max	0.971	mean	0.737	
	CPU COO	min	0.721	max	1.802	mean	0.871	CPU CSR	min	2.732	max*	2.751	mean	2.743	
	CPU CSR	min	2.393	max	2.408	mean	2.404	GPU 64 COO	min	17.720	max	18.070	mean	17.911	
	GPU 64 COO	min	5.410	max	5.480	mean	5.453	CSR	min	29.600	max	30.500	mean	29.961	
	CPU COO	min	0.721	max	1.802	mean	0.871	CPU PAR	min	0.827	max	0.954	mean	0.913	
	CPU CSR	min	2.393	max	2.408	mean	2.404								
	GPU 64 COO	min	5.410	max	5.480	mean	5.453								

	H	min 10.776 max 10.778 mean 10.777	Row-Premute		
aft01.mtx				GPU 64 COO min 3.860 max 4.090 mean 4.001	
Regular				CSR min 9.520 max 10.340 mean 9.936	
				H min 11.161 max 11.167 mean 11.165	
	CPU COO min 0.735 max* 2.079 mean 1.069		Row-Gradient		
	CPU CSR min 3.132 max* 3.154 mean 3.145			GPU 64 COO min 4.010 max 4.240 mean 4.135	
	GPU 64 COO min 6.390 max* 6.610 mean 6.457			CSR min 5.890 max 11.350 mean 6.882	
	CSR min 19.990 max*23.250 mean 21.820			H min 10.246 max 10.262 mean 10.256	
	CPU PAR min 1.746 max* 1.865 mean 1.812		Column-Gradient		
	H min 7.811 max 7.811 mean 7.811			GPU 64 COO min 3.850 max 4.100 mean 4.012	
Row-Premute				CSR min 5.460 max 8.790 mean 6.005	
	CPU COO min 0.714 max 1.648 mean 0.840			H min 11.112 max 11.122 mean 11.117	
	CPU CSR min 2.864 max 2.892 mean 2.883		Row-Column-Permute		
	GPU 64 COO min 6.280 max 6.380 mean 6.329			GPU 64 COO min 3.850 max 4.080 mean 3.990	
	CSR min 17.980 max 19.700 mean 19.105			CSR min 5.420 max 6.760 mean 5.977	
	CPU PAR min 1.729 max 1.850 mean 1.782			H min 11.162 max*11.169 mean 11.165	
	H min 11.162 max 11.168 mean 11.165		bloweya.mtx		
Row-Gradient			Regular		
	CPU COO min 0.735 max 1.806 mean 0.878			GPU 64 COO min 0.000 max 0.000 mean 0.000	
	CPU CSR min 2.706 max 2.744 mean 2.726			CSR min 0.000 max 0.000 mean 0.000	
	GPU 64 COO min 6.390 max 6.500 mean 6.433			H min 7.205 max 7.205 mean 7.205	
	CSR min 19.780 max 22.870 mean 20.936		Row-Premute		
	CPU PAR min 1.710 max 1.865 mean 1.785			GPU 64 COO min 3.800 max 3.940 mean 3.875	
	H min 10.251 max 10.267 mean 10.257			CSR min 3.710 max 4.570 mean 4.399	
Column-Gradient				H min 11.025 max 11.031 mean 11.028	
	CPU COO min 0.728 max 1.792 mean 0.986		Row-Gradient		
	CPU CSR min 2.521 max 2.720 mean 2.703			GPU 64 COO min 3.800 max* 4.120 mean 3.962	
	GPU 64 COO min 6.280 max 6.370 mean 6.327			CSR min 4.340 max* 4.670 mean 4.546	
	CSR min 18.000 max 19.720 mean 19.040			H min 10.296 max 10.307 mean 10.300	
	CPU PAR min 1.649 max 1.741 mean 1.702		Column-Gradient		
	H min 11.113 max 11.121 mean 11.117			GPU 64 COO min 3.880 max 4.100 mean 3.978	
Row-Column-Permute				CSR min 4.240 max 4.570 mean 4.412	
	CPU COO min 0.714 max 1.525 mean 0.957			H min 10.881 max 10.886 mean 10.883	
	CPU CSR min 2.876 max 2.892 mean 2.884		Row-Column-Permute		
	GPU 64 COO min 6.280 max 6.370 mean 6.322			GPU 64 COO min 3.800 max 3.980 mean 3.885	
	CSR min 17.960 max 19.670 mean 18.670			CSR min 4.130 max 4.540 mean 4.399	
	CPU PAR min 1.667 max 1.754 mean 1.710			H min 11.025 max*11.033 mean 11.029	
	H min 11.162 max*11.168 mean 11.165		brainpc2.mtx		
TSOPF_RS_b39_c7.mtx			Regular		
Regular				GPU 64 COO min 0.000 max 0.000 mean 0.000	
	CPU COO min 0.771 max 0.793 mean 0.780			CSR min 0.000 max 0.000 mean 0.000	
	CPU CSR min 3.219 max* 3.232 mean 3.227			H min 7.478 max 7.478 mean 7.478	
	GPU 64 COO min 11.070 max*11.200 mean 11.142		Row-Premute		
	CSR min 37.050 max*42.100 mean 39.040			GPU 64 COO min 3.840 max* 6.750 mean 4.110	
	CPU PAR min 1.910 max 2.027 mean 1.982			CSR min 4.260 max* 4.500 mean 4.437	
	H min 7.304 max 7.304 mean 7.304			H min 9.809 max 9.813 mean 9.811	
Row-Premute			Row-Gradient		
	CPU COO min 0.701 max 0.722 mean 0.707			GPU 64 COO min 0.640 max 4.030 mean 3.864	
	CPU CSR min 2.931 max 2.952 mean 2.942			CSR min 4.270 max 4.470 mean 4.383	
	GPU 64 COO min 10.860 max 11.030 mean 10.928			H min 9.722 max 9.727 mean 9.724	
	CSR min 28.730 max 30.880 mean 29.483		Column-Gradient		
	CPU PAR min 1.760 max 1.922 mean 1.851			GPU 64 COO min 0.640 max 4.070 mean 3.898	
	H min 10.537 max 10.541 mean 10.539			CSR min 4.230 max 4.500 mean 4.386	
Row-Gradient				H min 10.368 max*10.372 mean 10.370	
	CPU COO min 0.747 max 0.808 mean 0.757		Row-Column-Permute		
	CPU CSR min 2.606 max 2.648 mean 2.624			GPU 64 COO min 3.980 max 4.110 mean 4.027	
	GPU 64 COO min 10.850 max 11.120 mean 10.999			CSR min 4.320 max 4.490 mean 4.437	
	CSR min 33.910 max 37.600 mean 35.909			H min 9.809 max 9.813 mean 9.811	
	CPU PAR min 2.154 max* 2.245 mean 2.203		c-47.mtx		
	H min 9.636 max 9.646 mean 9.642		Regular		
Column-Gradient				GPU 64 COO min 3.980 max* 4.080 mean 4.026	
	CPU COO min 0.718 max* 1.693 mean 0.802			CSR min 4.760 max 4.850 mean 4.812	
	CPU CSR min 2.502 max 2.585 mean 2.547			H min 8.364 max 8.364 mean 8.364	
	GPU 64 COO min 10.700 max 10.990 mean 10.804		Row-Premute		
	CSR min 27.230 max 29.380 mean 28.488			GPU 64 COO min 3.880 max 4.010 mean 3.942	
	CPU PAR min 2.128 max 2.227 mean 2.172			CSR min 4.040 max 4.900 mean 4.807	
	H min 11.131 max*11.222 mean 11.208			H min 10.059 max 10.063 mean 10.061	
Row-Column-Permute			Row-Gradient		
	CPU COO min 0.709 max 0.726 mean 0.716			GPU 64 COO min 3.900 max 4.050 mean 3.976	
	CPU CSR min 2.917 max 2.958 mean 2.940			CSR min 4.380 max 4.740 mean 4.630	
	GPU 64 COO min 10.840 max 11.030 mean 10.930			H min 10.201 max 10.228 mean 10.214	
	CSR min 28.780 max 30.810 mean 29.578		Column-Gradient		
	CPU PAR min 1.757 max 1.834 mean 1.792			GPU 64 COO min 3.860 max 3.990 mean 3.936	
	H min 10.537 max 10.540 mean 10.539			CSR min 4.350 max 4.610 mean 4.525	
				H min 11.204 max*11.241 mean 11.222	
			Row-Column-Permute		
				GPU 64 COO min 3.890 max 4.020 mean 3.953	
				CSR min 4.490 max* 4.920 mean 4.840	
				H min 10.058 max 10.063 mean 10.061	
10 ELLESMERE			case9.mtx		
aft01.mtx			Regular		
Regular					
	GPU 64 COO min 4.080 max* 4.280 mean 4.186				
	CSR min 9.660 max*12.660 mean 11.485				
	H min 7.811 max 7.811 mean 7.811				

Row-Premute	GPU 64 COO min 0.000 max 0.000 mean 0.000	lp_fit2d.mtx Regular	H min 10.250 max 10.255 mean 10.252
	CSR min 0.000 max 0.000 mean 0.000		
	H min 7.380 max 7.380 mean 7.380		
Row-Gradient	GPU 64 COO min 4.820 max 4.940 mean 4.859	Row-Premute	GPU 64 COO min 4.360 max* 4.640 mean 4.515
	CSR min 5.080 max 6.520 mean 6.342		CSR min 10.080 max 10.900 mean 10.491
	H min 10.042 max 10.047 mean 10.044		H min 11.109 max 11.109 mean 11.109
Column-Gradient	GPU 64 COO min 4.810 max* 4.940 mean 4.876	Row-Gradient	GPU 64 COO min 4.170 max 4.630 mean 4.476
	CSR min 6.100 max* 6.560 mean 6.307		CSR min 0.910 max 10.910 mean 10.257
	H min 9.681 max 9.704 mean 9.694		H min 11.098 max 11.104 mean 11.101
Row-Column-Permute	GPU 64 COO min 4.810 max 4.930 mean 4.869	Column-Gradient	GPU 64 COO min 4.370 max 4.630 mean 4.529
	CSR min 4.820 max 6.460 mean 6.208		CSR min 10.030 max 10.970 mean 10.624
	H min 10.554 max*10.661 mean 10.638		H min 11.109 max 11.109 mean 11.109
cvxqp3.mtx Regular	GPU 64 COO min 4.810 max 4.940 mean 4.864	Row-Column-Permute	GPU 64 COO min 4.250 max 4.640 mean 4.499
	CSR min 5.930 max 6.520 mean 6.379		CSR min 8.510 max*11.010 mean 10.505
	H min 10.041 max 10.047 mean 10.044		H min 11.328 max*11.333 mean 11.331
Row-Premute	GPU 64 COO min 3.350 max* 3.590 mean 3.483	lp_osa_07.mtx Regular	GPU 64 COO min 4.350 max 4.640 mean 4.511
	CSR min 5.430 max* 9.260 mean 8.333		CSR min 10.040 max 10.790 mean 10.468
	H min 8.646 max 8.646 mean 8.646		H min 11.097 max 11.106 mean 11.101
Row-Gradient	GPU 64 COO min 3.230 max 3.480 mean 3.371	Row-Premute	GPU 64 COO min 0.460 max* 3.640 mean 3.456
	CSR min 7.560 max 8.220 mean 7.900		CSR min 5.570 max* 8.530 mean 8.106
	H min 11.027 max 11.033 mean 11.030		H min 8.412 max 8.412 mean 8.412
Column-Gradient	GPU 64 COO min 3.240 max 3.510 mean 3.396	Row-Gradient	GPU 64 COO min 3.140 max 3.450 mean 3.367
	CSR min 6.990 max 7.890 mean 7.574		CSR min 7.600 max 8.070 mean 7.853
	H min 11.060 max 11.069 mean 11.064		H min 9.255 max 9.258 mean 9.256
Row-Column-Permute	GPU 64 COO min 3.240 max 3.480 mean 3.374	Column-Gradient	GPU 64 COO min 3.190 max 3.610 mean 3.509
	CSR min 6.980 max 7.900 mean 7.557		CSR min 0.000 max 8.260 mean 7.597
	H min 11.126 max*11.134 mean 11.130		H min 8.583 max 8.678 mean 8.670
ex19.mtx Regular	GPU 64 COO min 3.110 max 3.470 mean 3.365	Row-Column-Permute	GPU 64 COO min 3.330 max 3.500 mean 3.416
	CSR min 4.810 max 8.210 mean 7.742		CSR min 6.730 max 7.540 mean 7.199
	H min 11.026 max 11.032 mean 11.030		H min 9.542 max* 9.604 mean 9.581
Row-Premute	GPU 64 COO min 2.450 max* 2.610 mean 2.564	Maragal_6.mtx Regular	GPU 64 COO min 3.290 max 3.430 mean 3.365
	CSR min 4.490 max 4.760 mean 4.714		CSR min 7.390 max 8.060 mean 7.832
	H min 8.228 max 8.228 mean 8.228		H min 9.255 max 9.258 mean 9.256
Row-Gradient	GPU 64 COO min 2.000 max 2.040 mean 2.021	Row-Premute	GPU 64 COO min 4.160 max 4.310 mean 4.217
	CSR min 4.640 max 4.780 mean 4.733		CSR min 4.940 max 4.960 mean 4.956
	H min 11.835 max 11.840 mean 11.838		H min 9.930 max 9.930 mean 9.930
Column-Gradient	GPU 64 COO min 2.240 max 2.390 mean 2.329	Row-Gradient	GPU 64 COO min 4.220 max 4.240 mean 4.225
	CSR min 4.570 max* 4.850 mean 4.807		CSR min 4.750 max*13.040 mean 5.133
	H min 10.742 max 10.752 mean 10.747		H min 10.776 max 10.778 mean 10.777
Row-Column-Permute	GPU 64 COO min 2.010 max 2.050 mean 2.034	Column-Gradient	GPU 64 COO min 4.180 max* 4.450 mean 4.245
	CSR min 4.570 max 4.760 mean 4.701		CSR min 4.880 max 4.940 mean 4.915
	H min 11.872 max*11.881 mean 11.878		H min 11.259 max*11.302 mean 11.281
gen4.mtx Regular	GPU 64 COO min 2.000 max 2.040 mean 2.023	Row-Column-Permute	GPU 64 COO min 4.200 max 4.250 mean 4.236
	CSR min 0.770 max 4.780 mean 4.594		CSR min 4.800 max 4.890 mean 4.859
	H min 11.835 max 11.840 mean 11.838		H min 12.022 max 12.073 mean 12.051
Row-Premute	GPU 64 COO min 4.880 max 4.980 mean 4.900	mhd4800a.mtx Regular	GPU 64 COO min 4.210 max 4.230 mean 4.222
	CSR min 10.020 max*11.300 mean 10.716		CSR min 4.860 max 4.890 mean 4.887
	H min 9.234 max 9.234 mean 9.234		H min 10.776 max 10.778 mean 10.778
Row-Gradient	GPU 64 COO min 4.860 max 4.930 mean 4.890	Row-Premute	GPU 64 COO min 4.570 max* 4.710 mean 4.608
	CSR min 0.330 max 11.200 mean 10.038		CSR min 12.690 max*13.940 mean 13.369
	H min 10.249 max 10.254 mean 10.252		H min 7.132 max 7.132 mean 7.132
Column-Gradient	GPU 64 COO min 4.860 max* 4.990 mean 4.908	Row-Gradient	GPU 64 COO min 4.420 max 4.520 mean 4.445
	CSR min 9.160 max 11.240 mean 10.435		CSR min 10.520 max 10.880 mean 10.696
	H min 9.939 max 9.961 mean 9.947		H min 10.960 max*10.968 mean 10.963
Row-Column-Permute	GPU 64 COO min 4.780 max 4.880 mean 4.816	Column-Gradient	GPU 64 COO min 4.570 max 4.690 mean 4.605
	CSR min 7.770 max 10.570 mean 9.407		CSR min 4.550 max 13.350 mean 12.479
	H min 10.851 max*10.876 mean 10.864		H min 9.508 max 9.527 mean 9.520
gen4.mtx Regular	GPU 64 COO min 4.850 max 4.950 mean 4.886	Row-Column-Permute	GPU 64 COO min 4.430 max 4.530 mean 4.461
	CSR min 10.220 max 11.280 mean 10.748		CSR min 10.250 max 10.940 mean 10.603
			H min 10.934 max 10.945 mean 10.939

Row-Column-Permute	GPU 64 C00 min 4.420 max 4.520 mean 4.450 CSR min 7.380 max 10.900 mean 10.598 H min 10.959 max 10.967 mean 10.963				GPU 64 C00 min 4.580 max 4.870 mean 4.756 CSR min 5.630 max 6.180 mean 6.055 H min 11.394 max*11.401 mean 11.397
mult_dcop_01.mtx Regular	GPU 64 C00 min 3.420 max 3.630 mean 3.555 CSR min 3.650 max 4.090 mean 3.814 H min 9.689 max 9.689 mean 9.689			OPF_6000.mtx Regular	GPU 64 C00 min 4.610 max 4.900 mean 4.780 CSR min 5.010 max 6.300 mean 6.113 H min 11.268 max 11.272 mean 11.270
Row-Premute	GPU 64 C00 min 3.450 max 3.580 mean 3.521 CSR min 3.610 max 4.150 mean 3.785 H min 10.738 max 10.742 mean 10.740			Row-Premute	GPU 64 C00 min 3.780 max* 3.920 mean 3.864 CSR min 4.270 max 4.360 mean 4.332 H min 8.799 max 8.799 mean 8.799
Row-Gradient	GPU 64 C00 min 3.510 max* 3.660 mean 3.579 CSR min 3.650 max 4.160 mean 3.806 H min 10.576 max 10.585 mean 10.580			Row-Gradient	GPU 64 C00 min 3.770 max 3.870 mean 3.821 CSR min 3.970 max*11.050 mean 4.439 H min 11.872 max 11.877 mean 11.875
Column-Gradient	GPU 64 C00 min 3.460 max 3.650 mean 3.584 CSR min 3.660 max* 4.240 mean 3.799 H min 10.826 max*10.842 mean 10.836			Column-Gradient	GPU 64 C00 min 3.700 max 3.870 mean 3.795 CSR min 4.330 max 4.440 mean 4.403 H min 11.109 max 11.116 mean 11.113
Row-Column-Permute	GPU 64 C00 min 3.470 max 3.580 mean 3.532 CSR min 3.600 max 3.980 mean 3.743 H min 10.738 max 10.742 mean 10.740			Row-Column-Permute	GPU 64 C00 min 3.690 max 3.870 mean 3.804 CSR min 4.260 max 4.340 mean 4.308 H min 12.041 max*12.045 mean 12.043
mult_dcop_02.mtx Regular	GPU 64 C00 min 3.390 max 3.660 mean 3.585 CSR min 0.960 max 4.330 mean 4.162 H min 9.689 max 9.689 mean 9.689			shermanACb.mtx Regular	GPU 64 C00 min 3.780 max 3.860 mean 3.819 CSR min 4.090 max 4.290 mean 4.259 H min 11.873 max 11.877 mean 11.876
Row-Premute	GPU 64 C00 min 3.310 max 3.600 mean 3.488 CSR min 0.620 max 4.290 mean 4.132 H min 10.738 max 10.743 mean 10.740			Row-Premute	GPU 64 C00 min 2.920 max* 3.140 mean 3.048 CSR min 5.550 max 5.980 mean 5.803 H min 8.600 max 8.600 mean 8.600
Row-Gradient	GPU 64 C00 min 3.310 max* 3.670 mean 3.593 CSR min 4.130 max* 4.430 mean 4.331 H min 10.576 max 10.584 mean 10.580			Row-Gradient	GPU 64 C00 min 2.760 max 3.020 mean 2.898 CSR min 2.660 max 5.830 mean 5.632 H min 10.377 max 10.381 mean 10.379
Column-Gradient	GPU 64 C00 min 0.550 max 3.660 mean 3.486 CSR min 3.890 max 4.410 mean 4.275 H min 10.831 max*10.843 mean 10.836			Column-Gradient	GPU 64 C00 min 2.800 max 3.040 mean 2.944 CSR min 5.330 max* 6.020 mean 5.742 H min 9.919 max 9.925 mean 9.922
Row-Column-Permute	GPU 64 C00 min 3.470 max 3.590 mean 3.542 CSR min 4.190 max 4.290 mean 4.242 H min 10.738 max 10.742 mean 10.740			Row-Column-Permute	GPU 64 C00 min 2.720 max 3.010 mean 2.926 CSR min 0.000 max 5.840 mean 5.513 H min 10.587 max*10.596 mean 10.591
mult_dcop_03.mtx Regular	GPU 64 C00 min 3.360 max* 3.660 mean 3.550 CSR min 3.650 max 4.090 mean 3.813 H min 9.689 max 9.689 mean 9.689			TSOPF_FS_b9_c6.mtx Regular	GPU 64 C00 min 2.780 max 3.030 mean 2.939 CSR min 4.860 max 5.810 mean 5.667 H min 10.376 max 10.382 mean 10.379
Row-Premute	GPU 64 C00 min 3.450 max 3.580 mean 3.521 CSR min 3.610 max 4.160 mean 3.784 H min 10.738 max 10.743 mean 10.740			Row-Premute	GPU 64 C00 min 0.000 max 0.000 mean 0.000 CSR min 0.000 max 0.000 mean 0.000 H min 7.380 max 7.380 mean 7.380
Row-Gradient	GPU 64 C00 min 3.470 max 3.660 mean 3.572 CSR min 3.640 max 4.190 mean 3.809 H min 10.572 max 10.584 mean 10.580			Row-Gradient	GPU 64 C00 min 4.540 max 4.940 mean 4.874 CSR min 6.280 max 6.520 mean 6.403 H min 10.042 max 10.047 mean 10.044
Column-Gradient	GPU 64 C00 min 3.430 max 3.650 mean 3.562 CSR min 3.670 max* 4.290 mean 3.793 H min 10.828 max*10.840 mean 10.834			Column-Gradient	GPU 64 C00 min 4.830 max 4.930 mean 4.875 CSR min 5.790 max* 6.560 mean 6.289 H min 9.675 max 9.706 mean 9.692
Row-Column-Permute	GPU 64 C00 min 3.370 max 3.610 mean 3.502 CSR min 3.610 max 3.970 mean 3.744 H min 10.738 max 10.741 mean 10.740			Row-Column-Permute	GPU 64 C00 min 4.790 max* 4.960 mean 4.880 CSR min 5.760 max 6.450 mean 6.204 H min 10.601 max*10.661 mean 10.626
OPF_3754.mtx Regular	GPU 64 C00 min 4.700 max* 4.930 mean 4.842 CSR min 6.230 max* 6.600 mean 6.411 H min 8.393 max 8.393 mean 8.393			TSOPF_RS_b39_c7.mtx Regular	GPU 64 C00 min 4.330 max 4.950 mean 4.845 CSR min 5.740 max 6.500 mean 6.375 H min 10.041 max 10.046 mean 10.044
Row-Premute	GPU 64 C00 min 4.620 max 4.890 mean 4.787 CSR min 5.780 max 6.310 mean 6.192 H min 11.265 max 11.272 mean 11.269			Row-Premute	GPU 64 C00 min 4.300 max* 4.430 mean 4.364 CSR min 4.480 max 4.750 mean 4.716 H min 7.304 max 7.304 mean 7.304
Row-Gradient	GPU 64 C00 min 4.570 max 4.870 mean 4.776 CSR min 5.770 max 6.510 mean 6.302 H min 10.464 max 10.473 mean 10.468			Row-Gradient	GPU 64 C00 min 4.260 max 4.400 mean 4.353 CSR min 4.490 max 4.770 mean 4.734 H min 10.536 max 10.541 mean 10.539
Column-Gradient					GPU 64 C00 min 3.970 max 4.420 mean 4.338

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mult_dcop_03.mtx
Regular

Row-Premute	H	GPU 64 COO min	5.140	max*	5.140	mean	5.140
		CSR min	10.340	max*10.390	mean	10.365	
		min	9.689	max	9.689	mean	9.689
Row-Gradient	H	GPU 64 COO min	4.970	max	4.990	mean	4.980
		CSR min	9.420	max	9.430	mean	9.425
		min	10.739	max	10.739	mean	10.739
Column-Gradient	H	GPU 64 COO min	5.080	max	5.090	mean	5.085
		CSR min	9.720	max	10.300	mean	10.010
		min	10.579	max	10.582	mean	10.580
Row-Column-Permute	H	GPU 64 COO min	5.030	max	5.120	mean	5.075
		CSR min	9.330	max	9.770	mean	9.550
		min	10.835	max*10.838	mean	10.836	
mult_dcop_03.mtx Regular	H	GPU 64 COO min	5.000	max	5.010	mean	5.005
		CSR min	7.580	max	9.460	mean	8.520
		min	10.739	max	10.741	mean	10.740
Row-Premute	H	GPU 64 COO min	5.140	max*	5.140	mean	5.140
		CSR min	10.340	max*10.390	mean	10.365	
		min	9.689	max	9.689	mean	9.689
Row-Gradient	H	GPU 64 COO min	4.970	max	4.990	mean	4.980
		CSR min	9.420	max	9.430	mean	9.425
		min	10.739	max	10.739	mean	10.739
Column-Gradient	H	GPU 64 COO min	5.080	max	5.090	mean	5.085
		CSR min	9.720	max	10.300	mean	10.010
		min	10.579	max	10.582	mean	10.580
Row-Column-Permute	H	GPU 64 COO min	5.030	max	5.120	mean	5.075
		CSR min	9.330	max	9.770	mean	9.550
		min	10.835	max*10.838	mean	10.836	
mult_dcop_03.mtx Regular	H	GPU 64 COO min	5.000	max	5.010	mean	5.005
		CSR min	7.580	max	9.460	mean	8.520
		min	10.739	max	10.741	mean	10.740
Row-Premute	H	GPU 64 COO min	5.130	max*	5.220	mean	5.142
		CSR min	7.250	max*	9.320	mean	7.722
		min	9.689	max	9.689	mean	9.689
Row-Gradient	H	GPU 64 COO min	4.980	max	5.030	mean	4.999
		CSR min	6.460	max	8.470	mean	6.950
		min	10.738	max	10.742	mean	10.740
Column-Gradient	H	GPU 64 COO min	5.070	max	5.140	mean	5.088
		CSR min	6.780	max	8.700	mean	7.268
		min	10.572	max	10.584	mean	10.580
Row-Column-Permute	H	GPU 64 COO min	4.980	max	5.030	mean	5.010
		CSR min	6.390	max	7.640	mean	6.982
		min	10.825	max*10.845	mean	10.836	
mult_dcop_01.mtx Regular	H	GPU 64 COO min	4.990	max	5.010	mean	4.997
		CSR min	6.300	max	7.160	mean	6.636
		min	10.738	max	10.743	mean	10.740
mult_dcop_01.mtx Regular	H	GPU 64 COO min	5.120	max*	5.140	mean	5.134
		CSR min	6.990	max*	9.230	mean	7.546
		min	9.689	max	9.689	mean	9.689

Row-Premute	GPU 64	COO	min	4.990	max	5.020	mean	5.004
		CSR	min	6.370	max	7.220	mean	6.771
	H		min	10.738	max	10.743	mean	10.740
Row-Gradient	GPU 64	COO	min	5.060	max	5.100	mean	5.082
		CSR	min	6.730	max	7.720	mean	7.317
	H		min	10.574	max	10.585	mean	10.580
Column-Gradient	GPU 64	COO	min	4.980	max	5.100	mean	5.012
		CSR	min	6.580	max	7.510	mean	7.054
	H		min	10.828	max	10.842	mean	10.835
Row-Column-Permute	GPU 64	COO	min	4.970	max	5.000	mean	4.986
		CSR	min	6.390	max	7.050	mean	6.677
	H		min	10.738	max	10.742	mean	10.740
mult_dcop_02.mtx Regular	GPU 64	COO	min	5.120	max	5.140	mean	5.133
		CSR	min	6.950	max	7.590	mean	7.336
	H		min	9.689	max	9.689	mean	9.689
Row-Premute	GPU 64	COO	min	4.970	max	4.990	mean	4.984
		CSR	min	6.440	max	7.110	mean	6.719
	H		min	10.738	max	10.742	mean	10.740
Row-Gradient	GPU 64	COO	min	5.070	max*	5.150	mean	5.086
		CSR	min	6.650	max*	7.930	mean	7.304
	H		min	10.574	max	10.587	mean	10.580
Column-Gradient	GPU 64	COO	min	4.980	max	5.040	mean	5.012
		CSR	min	6.520	max	7.650	mean	7.139
	H		min	10.829	max*	10.846	mean	10.836
Row-Column-Permute	GPU 64	COO	min	4.970	max	5.050	mean	4.983
		CSR	min	6.440	max	7.380	mean	6.779
	H		min	10.738	max	10.743	mean	10.740
lp_fit2d.mtx Regular	GPU 64	COO	min	3.960	max	3.960	mean	3.960
		CSR	min	6.360	max	7.450	mean	6.711
	H		min	11.109	max	11.109	mean	11.109
Row-Premute	GPU 64	COO	min	3.950	max*	3.980	mean	3.953
		CSR	min	6.330	max	7.400	mean	6.661
	H		min	11.098	max	11.104	mean	11.101
Row-Gradient	GPU 64	COO	min	3.960	max	3.980	mean	3.961
		CSR	min	6.270	max*	10.770	mean	7.017
	H		min	11.109	max	11.109	mean	11.109
Column-Gradient	GPU 64	COO	min	3.940	max	3.960	mean	3.950
		CSR	min	6.270	max	7.370	mean	6.696
	H		min	11.329	max*	11.334	mean	11.331
Row-Column-Permute	GPU 64	COO	min	3.950	max	3.960	mean	3.952
		CSR	min	6.180	max	7.420	mean	6.641
	H		min	11.098	max	11.105	mean	11.101
bloweya.mtx Regular	GPU 64	COO	min	0.000	max	0.000	mean	0.000
		CSR	min	0.000	max	0.000	mean	0.000
	H		min	7.205	max	7.205	mean	7.205
Row-Premute	GPU 64	COO	min	4.020	max	4.030	mean	4.023
		CSR	min	6.070	max	6.750	mean	6.340
	H		min	11.025	max	11.031	mean	11.028
Row-Gradient	GPU 64	COO	min	4.090	max*	4.160	mean	4.111
		CSR	min	5.980	max*	7.370	mean	6.678
	H		min	10.295	max	10.304	mean	10.300
Column-Gradient	GPU 64	COO	min	3.980	max	4.010	mean	3.995
		CSR	min	5.880	max	6.780	mean	6.295
	H		min	10.881	max*	10.887	mean	10.883
Row-Column-Permute	GPU 64	COO	min	4.020	max	4.030	mean	4.023
		CSR	min	5.970	max	6.420	mean	6.183
	H		min	11.025	max	11.033	mean	11.028

ex19.mtx Regular	Row-Permute	GPU 64 COO min 4.260 max* 4.270 mean 4.261 CSR min 6.440 max 7.640 mean 6.863 H min 8.412 max 8.412 mean 8.412	cvxqp3.mtx Regular	H min 10.377 max 10.381 mean 10.379
		GPU 64 COO min 4.200 max 4.200 mean 4.200 CSR min 6.020 max 7.030 mean 6.418 H min 9.255 max 9.257 mean 9.256		GPU 64 COO min 3.500 max* 3.540 mean 3.501 CSR min 11.860 max*13.100 mean 12.694 H min 8.646 max 8.646 mean 8.646
		GPU 64 COO min 4.210 max 4.240 mean 4.226 CSR min 6.070 max*10.050 mean 6.498 H min 8.607 max 8.678 mean 8.671		GPU 64 COO min 3.360 max 3.370 mean 3.365 CSR min 6.210 max 7.610 mean 6.631 H min 11.027 max 11.032 mean 11.030
Row-Gradient	Column-Gradient	GPU 64 COO min 4.170 max 4.190 mean 4.180 CSR min 5.610 max 7.300 mean 5.988 H min 9.534 max* 9.601 mean 9.585	Row-Permute	GPU 64 COO min 3.370 max 3.380 mean 3.376 CSR min 6.170 max 7.070 mean 6.499 H min 11.059 max 11.068 mean 11.064
		GPU 64 COO min 4.190 max 4.190 mean 4.190 CSR min 6.070 max 7.000 mean 6.386 H min 9.255 max 9.257 mean 9.256		GPU 64 COO min 3.350 max 3.390 mean 3.371 CSR min 6.150 max 7.180 mean 6.531 H min 11.125 max*11.133 mean 11.130
		GPU 64 COO min 6.140 max* 6.180 mean 6.159 CSR min 12.780 max*14.400 mean 13.328 H min 8.228 max 8.228 mean 8.228		GPU 64 COO min 3.350 max 3.380 mean 3.364 CSR min 6.040 max 7.440 mean 6.603 H min 11.028 max 11.033 mean 11.030
Row-Gradient	Column-Gradient	GPU 64 COO min 5.820 max 5.850 mean 5.833 CSR min 9.870 max 11.070 mean 10.372 H min 11.836 max 11.840 mean 11.838	case9.mtx Regular	GPU 64 COO min 0.000 max 0.000 mean 0.000 CSR min 0.000 max 0.000 mean 0.000 H min 7.380 max 7.380 mean 7.380
		GPU 64 COO min 6.070 max 6.120 mean 6.104 CSR min 11.290 max 12.760 mean 12.088 H min 10.743 max 10.752 mean 10.748		GPU 64 COO min 4.130 max 4.170 mean 4.134 CSR min 6.180 max* 9.200 mean 6.796 H min 10.041 max 10.046 mean 10.044
		GPU 64 COO min 5.760 max 5.840 mean 5.813 CSR min 9.710 max 14.220 mean 10.376 H min 11.873 max*11.882 mean 11.878		GPU 64 COO min 4.150 max* 4.220 mean 4.163 CSR min 6.410 max 7.500 mean 6.816 H min 9.682 max 9.706 mean 9.693
Row-Column-Permute	Row-Column-Permute	GPU 64 COO min 5.810 max 5.860 mean 5.838 CSR min 9.920 max 10.820 mean 10.240 H min 11.836 max 11.841 mean 11.838	Row-Column-Permute	GPU 64 COO min 4.080 max 4.110 mean 4.096 CSR min 6.020 max 7.220 mean 6.309 H min 10.597 max*10.658 mean 10.631
		GPU 64 COO min 0.000 max 0.000 mean 0.000 CSR min 0.000 max 0.000 mean 0.000 H min 7.478 max 7.478 mean 7.478		GPU 64 COO min 4.120 max 4.140 mean 4.130 CSR min 6.210 max 7.200 mean 6.609 H min 10.041 max 10.046 mean 10.044
		GPU 64 COO min 4.760 max 4.790 mean 4.773 CSR min 6.930 max 7.780 mean 7.310 H min 9.810 max 9.813 mean 9.811		GPU 64 COO min 0.000 max 0.000 mean 0.000 CSR min 0.000 max 0.000 mean 0.000 H min 7.380 max 7.380 mean 7.380
Row-Gradient	Column-Gradient	GPU 64 COO min 4.820 max* 4.840 mean 4.831 CSR min 7.220 max 8.290 mean 7.583 H min 9.721 max 9.725 mean 9.723	TSOPF_FS_b9_c6.mtx Regular	GPU 64 COO min 4.120 max 4.140 mean 4.129 CSR min 6.170 max 7.160 mean 6.664 H min 10.041 max 10.045 mean 10.043
		GPU 64 COO min 4.760 max 4.820 mean 4.779 CSR min 6.870 max* 8.300 mean 7.393 H min 10.368 max*10.373 mean 10.370		GPU 64 COO min 4.150 max* 4.180 mean 4.162 CSR min 6.420 max 7.360 mean 6.723 H min 9.682 max 9.706 mean 9.693
		GPU 64 COO min 4.750 max 4.780 mean 4.765 CSR min 6.940 max 7.580 mean 7.298 H min 9.809 max 9.814 mean 9.811		GPU 64 COO min 4.080 max 4.120 mean 4.096 CSR min 5.880 max 7.090 mean 6.403 H min 10.611 max*10.660 mean 10.637
Row-Column-Permute	Row-Column-Permute	GPU 64 COO min 4.090 max* 4.130 mean 4.112 CSR min 6.320 max* 7.200 mean 6.779 H min 8.600 max 8.600 mean 8.600	OPF_6000.mtx Regular	GPU 64 COO min 4.130 max 4.140 mean 4.130 CSR min 6.330 max* 7.390 mean 6.695 H min 10.042 max 10.047 mean 10.044
		GPU 64 COO min 4.020 max 4.050 mean 4.036 CSR min 5.670 max 6.460 mean 6.014 H min 10.376 max 10.382 mean 10.379		GPU 64 COO min 7.270 max* 7.370 mean 7.293 CSR min 12.890 max*14.500 mean 13.566 H min 8.799 max 8.799 mean 8.799
		GPU 64 COO min 4.050 max 4.100 mean 4.074 CSR min 5.580 max 6.420 mean 5.996 H min 9.918 max 9.924 mean 9.921		GPU 64 COO min 6.640 max 6.720 mean 6.678 CSR min 9.680 max 11.600 mean 10.040 H min 11.873 max 11.877 mean 11.875
Row-Column-Permute	Row-Column-Permute	GPU 64 COO min 4.010 max 4.080 mean 4.033 CSR min 0.000 max 6.320 mean 5.527 H min 10.543 max*10.595 mean 10.589	Column-Gradient	GPU 64 COO min 7.090 max 7.140 mean 7.122 CSR min 11.250 max 13.030 mean 12.142 H min 11.110 max 11.117 mean 11.114
		GPU 64 COO min 4.020 max 4.050 mean 4.036 CSR min 5.670 max 6.510 mean 6.092		GPU 64 COO min 6.590 max 6.710 mean 6.644 CSR min 9.400 max 13.140 mean 9.991 H min 12.040 max*12.046 mean 12.043

Row-Column-Permute	GPU 64 COO min 6.640 max 6.710 mean 6.679 CSR min 9.690 max 10.740 mean 10.050 H min 11.874 max 11.877 mean 11.875		Row-Column-Permute	GPU 64 COO min 3.240 max 3.260 mean 3.249 CSR min 5.090 max 8.660 mean 5.546 H min 10.853 max 10.873 mean 10.864
OPF_3754.mtx Regular	GPU 64 COO min 4.430 max 4.450 mean 4.443 CSR min 9.710 max 13.000 mean 11.377 H min 8.393 max 8.393 mean 8.393		Maragal_6.mtx Regular	GPU 64 COO min 3.290 max 3.320 mean 3.296 CSR min 5.190 max 7.550 mean 5.659 H min 10.249 max 10.255 mean 10.252
Row-Premute	GPU 64 COO min 4.230 max 4.250 mean 4.240 CSR min 7.430 max 8.750 mean 7.986 H min 11.266 max 11.272 mean 11.269		Row-Premute	GPU 64 COO min 10.580 max 10.620 mean 10.599 CSR min 15.620 max 16.470 mean 15.832 H min 9.930 max 9.930 mean 9.930
Row-Gradient	GPU 64 COO min 4.370 max 4.420 mean 4.382 CSR min 8.160 max 9.470 mean 8.682 H min 10.462 max 10.473 mean 10.468		Row-Gradient	GPU 64 COO min 10.340 max 10.430 mean 10.362 CSR min 12.880 max 13.340 mean 13.057 H min 10.777 max 10.778 mean 10.777
Column-Gradient	GPU 64 COO min 4.210 max 4.240 mean 4.227 CSR min 7.160 max 8.080 mean 7.595 H min 11.394 max 11.401 mean 11.398		Column-Gradient	GPU 64 COO min 10.650 max 10.740 mean 10.688 CSR min 12.310 max 13.670 mean 12.562 H min 11.247 max 11.300 mean 11.281
Row-Column-Permute	GPU 64 COO min 4.230 max 4.250 mean 4.243 CSR min 7.230 max 8.940 mean 8.056 H min 11.264 max 11.271 mean 11.269		Row-Column-Permute	GPU 64 COO min 10.340 max 10.440 mean 10.398 CSR min 9.480 max 10.110 mean 9.782 H min 12.023 max 12.069 mean 12.047
c-47.mtx Regular	GPU 64 COO min 5.320 max 5.340 mean 5.329 CSR min 8.890 max 9.590 mean 9.249 H min 8.364 max 8.364 mean 8.364		aft01.mtx Regular	GPU 64 COO min 10.330 max 10.380 mean 10.356 CSR min 12.840 max 13.530 mean 13.119 H min 10.776 max 10.778 mean 10.777
Row-Premute	GPU 64 COO min 5.240 max 5.250 mean 5.241 CSR min 7.790 max 8.890 mean 8.214 H min 10.059 max 10.063 mean 10.061		Row-Premute	GPU 64 COO min 3.680 max 3.690 mean 3.688 CSR min 13.860 max 14.830 mean 14.560 H min 7.811 max 7.811 mean 7.811
Row-Gradient	GPU 64 COO min 5.230 max 5.260 mean 5.242 CSR min 7.080 max 8.050 mean 7.673 H min 10.206 max 10.226 mean 10.218		Row-Gradient	GPU 64 COO min 3.510 max 3.530 mean 3.513 CSR min 6.420 max 10.520 mean 7.265 H min 11.161 max 11.170 mean 11.165
Column-Gradient	GPU 64 COO min 5.080 max 5.120 mean 5.105 CSR min 5.780 max 6.970 mean 6.359 H min 11.205 max 11.233 mean 11.222		Column-Gradient	GPU 64 COO min 3.630 max 3.670 mean 3.643 CSR min 10.760 max 13.510 mean 12.199 H min 10.248 max 10.265 mean 10.258
Row-Column-Permute	GPU 64 COO min 5.220 max 5.250 mean 5.227 CSR min 7.860 max 8.710 mean 8.247 H min 10.059 max 10.064 mean 10.061		Row-Column-Permute	GPU 64 COO min 3.510 max 3.520 mean 3.519 CSR min 6.490 max 11.230 mean 7.645 H min 11.112 max 11.121 mean 11.117
mhd4800a.mtx Regular	GPU 64 COO min 3.090 max 3.100 mean 3.098 CSR min 11.570 max 12.290 mean 12.092 H min 7.132 max 7.132 mean 7.132		TSOPF_RS_b39_c7.mtx Regular	GPU 64 COO min 3.510 max 3.540 mean 3.515 CSR min 6.510 max 11.650 mean 7.311 H min 11.161 max 11.168 mean 11.165
Row-Premute	GPU 64 COO min 3.020 max 3.020 mean 3.020 CSR min 5.560 max 7.270 mean 6.007 H min 10.959 max 10.968 mean 10.963		Row-Premute	GPU 64 COO min 5.970 max 6.010 mean 5.988 CSR min 12.470 max 21.120 mean 13.816 H min 7.304 max 7.304 mean 7.304
Row-Gradient	GPU 64 COO min 3.080 max 3.100 mean 3.088 CSR min 10.250 max 12.150 mean 11.340 H min 9.509 max 9.528 mean 9.520		Row-Gradient	GPU 64 COO min 5.840 max 5.870 mean 5.856 CSR min 10.780 max 15.810 mean 11.425 H min 10.537 max 10.540 mean 10.539
Column-Gradient	GPU 64 COO min 3.020 max 3.050 mean 3.026 CSR min 5.530 max 10.580 mean 6.432 H min 10.933 max 10.946 mean 10.939		Column-Gradient	GPU 64 COO min 5.950 max 6.000 mean 5.975 CSR min 11.520 max 17.250 mean 12.799 H min 9.638 max 9.646 mean 9.641
Row-Column-Permute	GPU 64 COO min 3.020 max 3.020 mean 3.020 CSR min 5.510 max 6.830 mean 6.136 H min 10.959 max 10.967 mean 10.963		Row-Column-Permute	GPU 64 COO min 5.790 max 5.860 mean 5.827 CSR min 10.500 max 14.080 mean 11.237 H min 11.128 max 11.223 mean 11.209
gen4.mtx Regular	GPU 64 COO min 3.300 max 3.320 mean 3.308 CSR min 5.250 max 6.340 mean 5.705 H min 9.234 max 9.234 mean 9.234		mult_dcop_03.mtx Regular	GPU 64 COO min 5.850 max 5.870 mean 5.855 CSR min 10.790 max 15.250 mean 11.718 H min 10.537 max 10.541 mean 10.539
Row-Premute	GPU 64 COO min 3.290 max 3.310 mean 3.299 CSR min 5.190 max 7.420 mean 5.683 H min 10.249 max 10.254 mean 10.252		Row-Premute	GPU 64 COO min 5.130 max 5.220 mean 5.142 CSR min 7.250 max 9.320 mean 7.722 H min 9.689 max 9.689 mean 9.689
Row-Gradient	GPU 64 COO min 3.300 max 3.310 mean 3.301 CSR min 5.370 max 6.310 mean 5.659 H min 9.934 max 9.958 mean 9.948		Row-Gradient	GPU 64 COO min 4.980 max 5.030 mean 4.999 CSR min 6.460 max 8.470 mean 6.950 H min 10.738 max 10.742 mean 10.740
Column-Gradient				GPU 64 COO min 5.070 max 5.140 mean 5.088

Column-Gradient	H	CSR min	6.780	max	8.700	mean	7.268
		min	10.572	max	10.584	mean	10.580
	GPU 64	C00 min	4.980	max	5.030	mean	5.010
		CSR min	6.390	max	7.640	mean	6.982
Row-Column-Permute	H	min	10.825	max	10.845	mean	10.836
		GPU 64 C00 min	4.990	max	5.010	mean	4.997
		CSR min	6.300	max	7.160	mean	6.636
		H min	10.738	max	10.743	mean	10.740

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