

Randomization of Sparse Matrix by Vector Multiplication

ABHISHEK JAIN, ISMAIL BUSTANY, and PAOLO D'ALBERTO

A sparse matrix by vector multiplication (SpMV) is simplified by the matrix non-zero elements and how we store them. There are many SpMV applications, many matrix storage formats, and thus algorithms. However, there is no optimality without considering the architecture: for example, the CPU is one among many.

By nature, randomization is resilient to counter techniques, thus suitable to avoid worst case scenarios because we tend to reduce to an average case; however, randomization does to the best case scenario the same thing it does to the worst case, it can nudge the optimal solution off. Like preconditioning, randomization is advantageous when the matrix is reused or a constant such as in the power method, Krylov's space, or convolutions for image classifications. Differently from preconditioning we do not change the values of the matrix, we randomize row and column of the matrix. We shall show that randomization 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

The obvious questions are what is randomization and why would we use it? We shall provide formal definitions in the following sections, in this context, we randomly permute rows and column of a sparse matrix before a (sparse) matrix by a (dense) vector operation. We do this because randomization is the poor man's preconditioning and we do not mean it in a pejorative sense.

Preconditioning is a method to help the convergence of an iterative solution, for example a sequence of matrix by vector operations. Each iteration does a better job in searching the space and converging to a solution. In general, it means better numerical properties and well defined properties of the matrix itself. It does not mean that each iteration is faster. We want to make each iteration faster. From a mathematical and scientific point of view may seem uninteresting. From the engineering and deployment point of view is just the beginning.

There is a common thread in the scientific community to faster computations: multi-core systems. These are composed by multi-cores processors and GPUs. The main goal is a balanced work distribution and, when applicable, minimal communication [3, 4]. When storage strategy and algorithms must be considered together then GPUs provide the work horse for the current trust and research [1]. This research is towards optimal solutions and the authors strive for a clear and complete understanding of the software–hardware relation, and usually the hardware is composed of symmetric computational units. Interestingly, the SpMV's space and time complexity, which are small, may not warrant more

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performance because we end up using only one thousandth the capacity of the hardware. We may deploy efficient solutions: not necessarily faster but overall tailored for this.

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 **MISSING CITATION** []. Most of the existing accelerators saturates relatively low memory bandwidth available on FPGA platforms (less than 80 GB/s) **MISSING CITATION** []. 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. For example, Microsoft’s implementation of SpMV uses an FPGA platform which has only 2 DDR2-400 memory with a resulting bandwidth of 6.4 GB/s **MISSING CITATION** []. The accelerator is running at 100 MHz, it reads 64 Bytes of data every cycle, which corresponds to 5 non-zeros 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, The Convey systems released Convey HC-1 FPGA platform with 16 DDR2-677 memories resulting in overall 80 GB/s memory bandwidth **MISSING CITATION** []. The accelerator logic is allowed to run 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 block for custom solutions is a multi-ported buffer used to store vector entries. During execution, multiple column indexes are used as addresses to read corresponding vector entries; we shall provide more details in Section 2. Designing a buffer with 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 and loss of bandwidth. For example, hashing techniques and data duplication are possible solutions. However another problem arise: when we distribute SpMV computations across p -nodes, some of the nodes finish early and k nodes finish later because of unbalanced load in row/column major traversal. This is common for matrices where few rows or columns are dense. The k nodes out of p finish late and refer to as *straggler nodes*. Using random permutation of column/row we are trying to balance the load across p workers so that there is no straggler. From this hardware prospective, randomization is an optimization and provide a clear context our current work.

At this stage, we have too many knobs and tools to tune: algorithms, data structures, and dedicated hardware (CPU, GPUs, Custom). This is a (very) hard problem and we are not here for the solution of the inverse problem: find the best Hardware-Software solution for the one matrix by vector product. We are here to provide tools, we may say naive tools, to help understand how the structure of the matrix may affect the HW-SW solution. Randomization, or versions of it, is already used by custom hardware to re-organize the data flow to reduce communications and computation bottle necks. We come to play in this arena to show *how* to use randomization if at all.

For the readers in the field of algorithms, sparse matrix by (dense) vector is basically a sorting algorithm. Bare with us, Sorting is a method to find if an element is in a list without prior or limited knowledge of the list contents. Sorting is used to prepare the matrix and to find elements in between sparse matrices and sparse vectors. In custom architectures, sorting networks are used for routing elements of the matrix and vector to the proper functional unit. Interestingly, The best sorting algorithm is a function of the distribution of elements. If you are stuck with a sorting algorithm and the wrong distribution, randomization may change the distribution, and you do not need to talk to any HW designer

We organize our work as follows: In Section 2, we define the matrix by vector operation; in Section 3, we define what we mean for randomization. We use randomization to create a uniform distribution in Section 5 and we measure uniformity by nothing else than 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, benchmarks, in Section 7, and the complete set of measures for an AMD CPU and GPUs system 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 $y_i = \sum_j M_{i,j} * x_j$ where $M_{i,j}=0$ are not even represented and stored. Most of the experimental results in Section 8 are based on the classic addition $(+)$ and multiplication $(*)$ in floating point precision using 64bits (i.e., double floating point precision). $SpMV$ based on semi-ring $(min, +)$ is a short path algorithm based on an adjacent matrix of a graph, and 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 $O(M + N) = 2nnz$. Of course, the definition of sparsity may vary. We represent the matrix \mathbb{M} by using the Coordinate COO or and the compressed sparse row CSR ¹ format. The COO represents the non-zero of a matrix by a triplet (i, j, val) , 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 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 row- i starts (i.e., if row i exists). We have that $M_{i,*}$ is stored in $V[ROW[i] : ROW[i + 1]]$ and the column are at $COL[ROW[i] : ROW[i + 1]]$ and sorted increasingly. The CSR takes $2 \times nnz + M$ space and a row vector of the matrix can be found in $O(1)$.

The computation as $y_i = \sum_j M_{i,j} * x_j$ is a sequence of dot products and the CSR representation is a natural:

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

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

The matrix row is contiguous (in memory) and contiguous rows are contiguous. The access of the (dense) vector \mathbf{x} could have no pattern. The COO format could use a little preparation: For example, we can sort the array by row and add row information to achieve the same properties of CSR ; however transposing a COO matrix is just a swap of the array ROW and COL . Think about matrix multiply. As today, each dot 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

¹a.k.a. Compressed row storage CRS.

could compute a sub set of the y_i and a clean data load balancing can go a long way. If we have a 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

We refer to *Randomization* as row or column permutations of the matrix \mathbb{M} (thus a permutation of \mathbf{y} and \mathbf{x}) and we choose these by a pseudo-random process. Why we want to introduce uncertainty? The sparsity of our matrix \mathbb{M} has a pattern representing the nature of the original problem; such a pattern may exploit the wrong computation for an architecture; we could break such a pattern so that the only property left is a uniform distribution (of some sort). We must avoid the worst case and we would opt for an average case instead and we could do this to a class of \mathbb{M} .

If we know the matrix \mathbb{M} and we know the architecture, preconditioning must be a better solution. Well, it is. If we run experiments long enough, we choose the best permutations 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). This is the culminating point of knowing and we must strive to it. 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 HW. We are after an understanding when randomization is just enough: we want to let the hardware do its best with the least effort, or at least with the appearance to be effortless. Also we shall show there are different flavors of random.

Interestingly, this work stems from a sincere surprise about randomization efficacy and its application on custom SpMV. Here, we want 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 reduces to a sorting and we know that different sparsity may require different algorithms. This is a lot to unpack but this translates to a better performance of the sequential algorithm without changing the algorithm or better HW utilization.

We will show that (different) randomness affects architectures and algorithms differently, making randomization a suitable optimization especially when the application and hardware are at odds, hardware 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 and the matrix has to be split into components. We want to show that this study uses common tool, open software tools and sometimes naive experiments; however, we can infer properties applicable to proprietary and custom solutions.

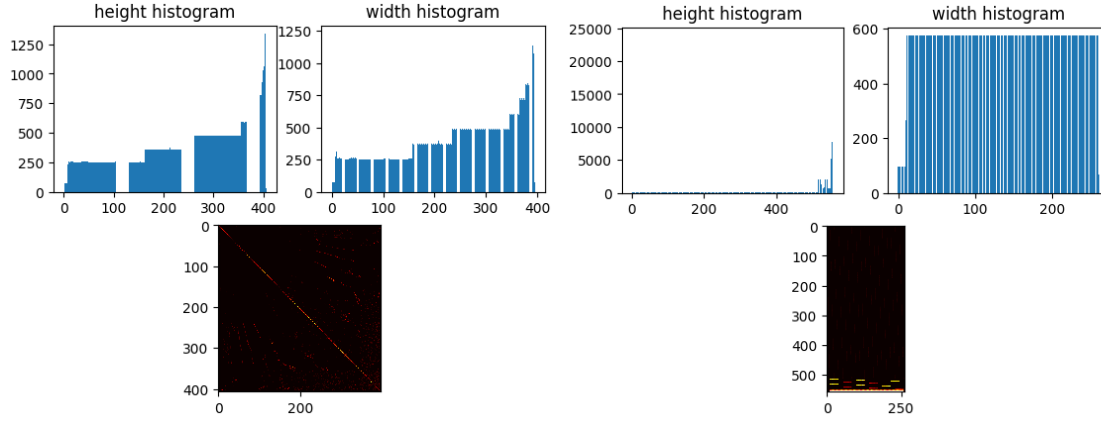


Fig. 1. Left: OPF 3754. Right: LP OSA 07. These are histograms where we represent normalized buckets and counts

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 than 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. There is no conceptual difference when the PDF represents a two dimensional distribution. Thus 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 only their probabilities. By construction, the matrices are quite different in sparsity and in shapes, however their entropy numbers are very 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 (which is a symmetric measure, please do not use Kullback-Leibler KL divergence) [2]. Or we could 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 a hierarchical entropy heat maps.

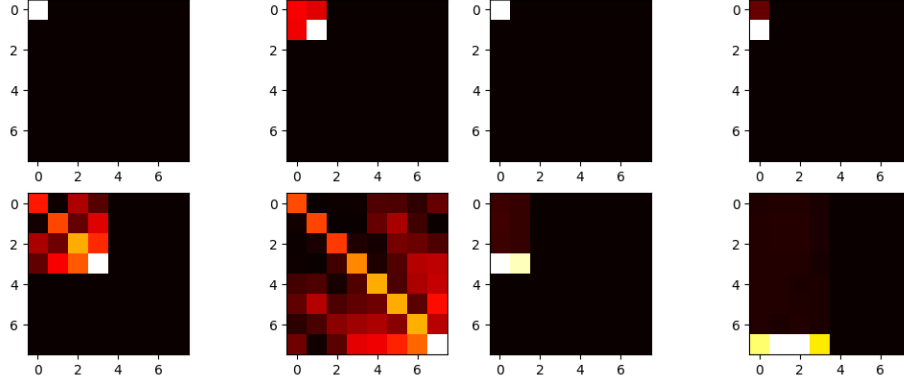


Fig. 2. Hierarchical 2D entropy for OPF 3754 (left) and LP OSA 07 (right).

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

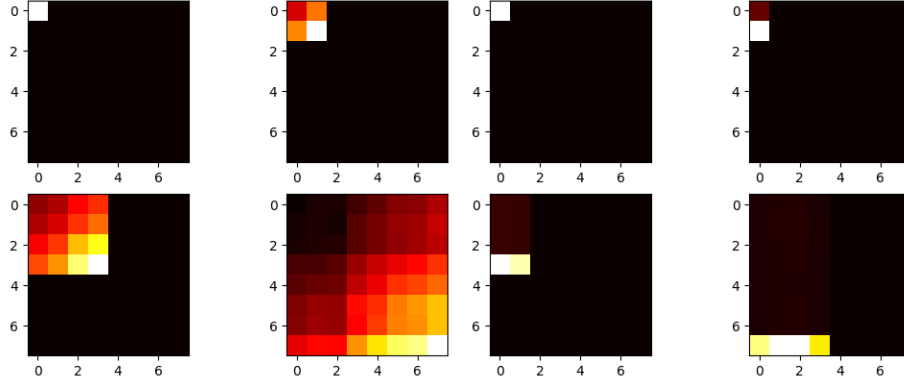


Fig. 3. Hierarchical 2D entropy after row and column random permutation for OPF 3754 (left) and LP OSA 07 (right).

166 In practice, permutations need some help especially for relatively large matrices. As you can see, the permutation
 167 affects locally the matrix. Of course, it depends on the implementation of the random permutation (we use numpy for
 168 this) but it is reasonable a slightly modified version of the original is still a random selection but unfortunately they seem
 169 more likely than they should. We need to compensate or help the randomization so that this current implementation
 170 does not get too lazy.

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 gradient operation 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.

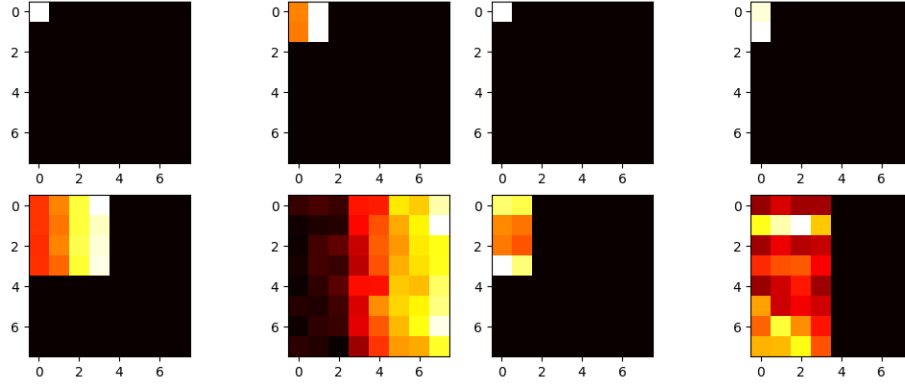


Fig. 4. Hierarchical 2D entropy after height gradient based shuffle and row random permutation for OPF 3754 (left) and LP OSA 07 (right).

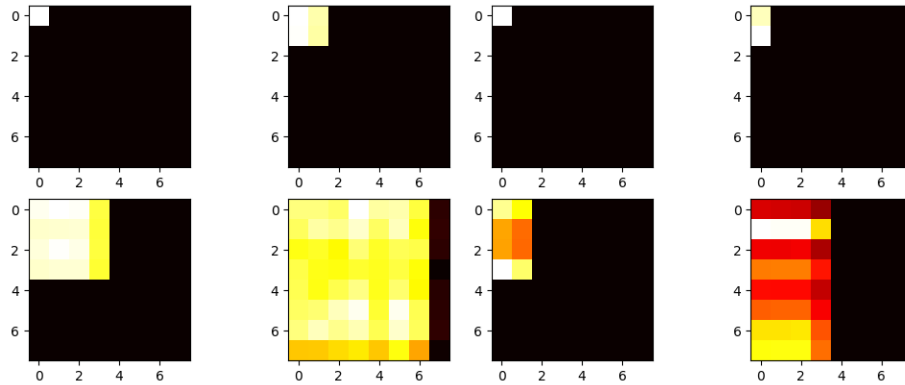


Fig. 5. Hierarchical 2D entropy after height and width gradient shuffle and row and column random permutation for OPF 3754 (left) and LP OSA 07 (right).

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 and 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 matrix without any permutation and thus is the regular; **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 CPU performance using COO and CSR SpMV algorithms for the matrix OPF 3754. We can see that the CSR algorithms are consistent and the Regular (i.e., the original) has always the best performance. For the COO, permutations introduce long tails, thus performance advantage.

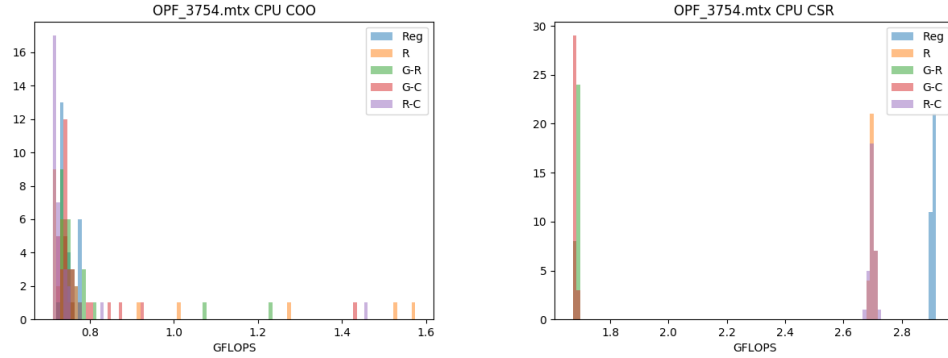


Fig. 6. CPU COO (left) and CPU CSR (left) for OPF 3754

In Figure 7, 8 and 9, randomization is harmful to the GPU implementation. The OPF 375 matrix is mostly diagonal, thus the vector \mathbf{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.

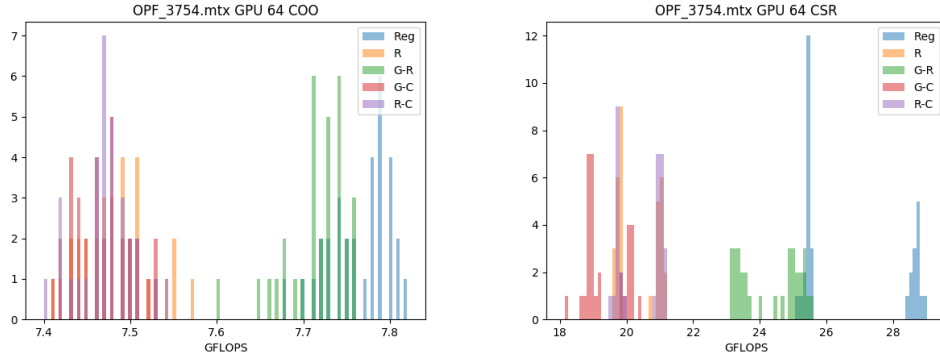


Fig. 7. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

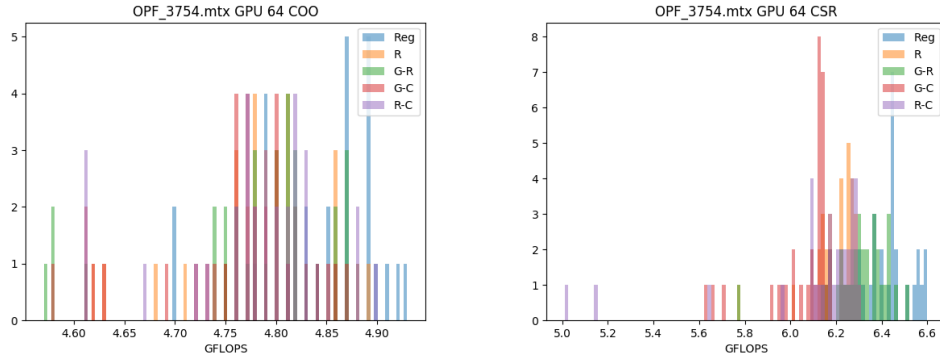


Fig. 8. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

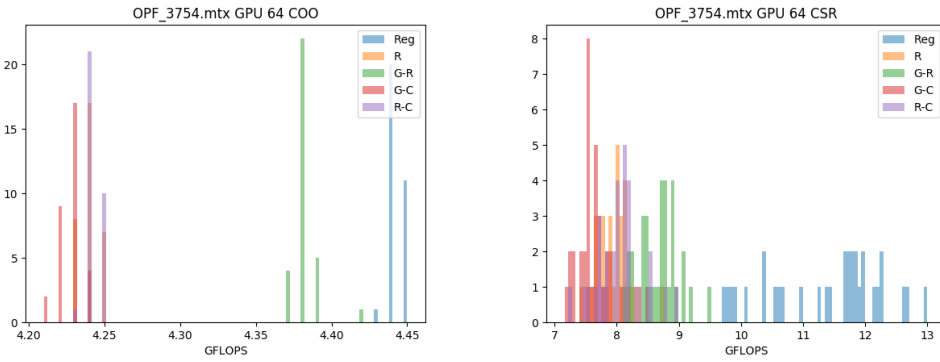


Fig. 9. Fiji, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

207 If we take the original matrix and split into part having the same number of rows, and execute them in parallel using
 208 different cores, we can see in Figure 10 that randomization is quite useful.

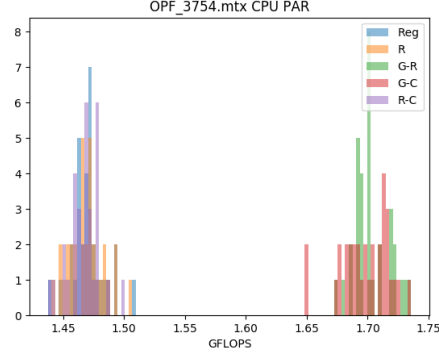


Fig. 10. Parallel CPU CSR for OPF 3754

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209 For matrix LP OSA 07, randomization helps clearly only for CPU CSR as we show in Figure 11

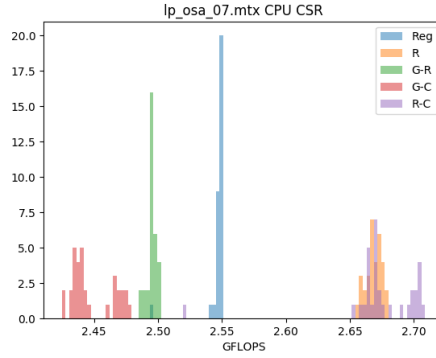


Fig. 11. CPU CSR for LP OSA 07

210 In Figure 12, 13, and 14, we can see that randomization is harmful but for one GPU, we can show that a single
 211 exception is possible (40% improvement).

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

215 What does it mean when randomization does not work? The matrices we use in this work are not chosen randomly
 216 (pun not intended), they are the matrices that are difficult to handle in our custom SpMV engines using a combination
 217 of sorting networks and systolic arrays. If randomization does not work in our simplified work bench, will not work in
 218 our specialized architecture because the reorganization of the matrix or the input and output vector does not have
 219 the necessary parallelism, data locality, and data streaming. We need to do something else. In this case disrupting the
 220 memory pattern is not sufficient. Thus, if we cannot beat the pattern, we must exploit it, well not in this work.

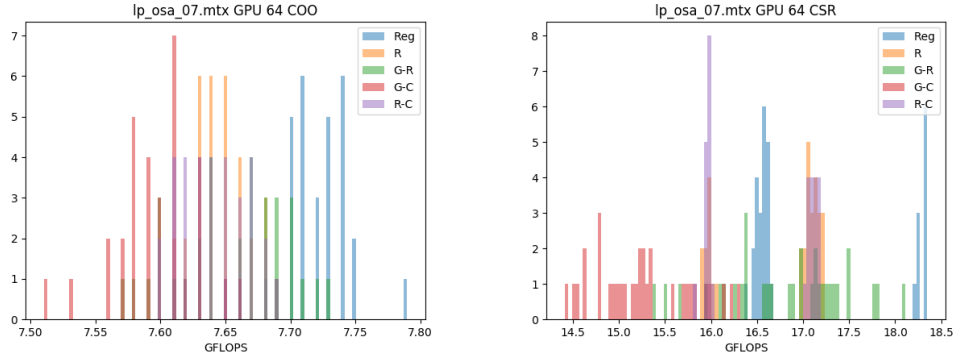


Fig. 12. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

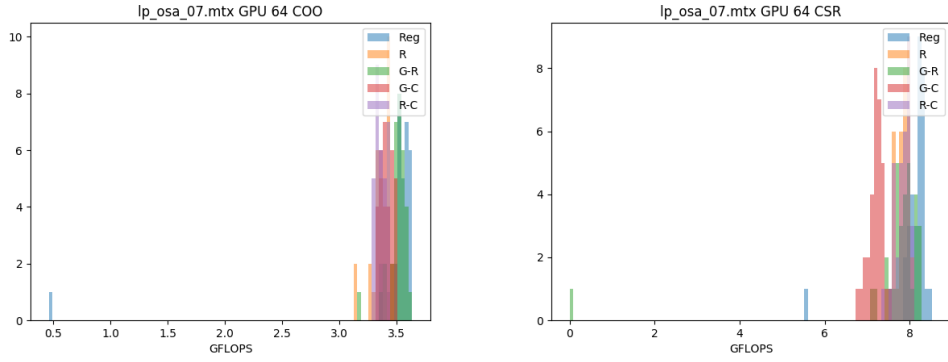


Fig. 13. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

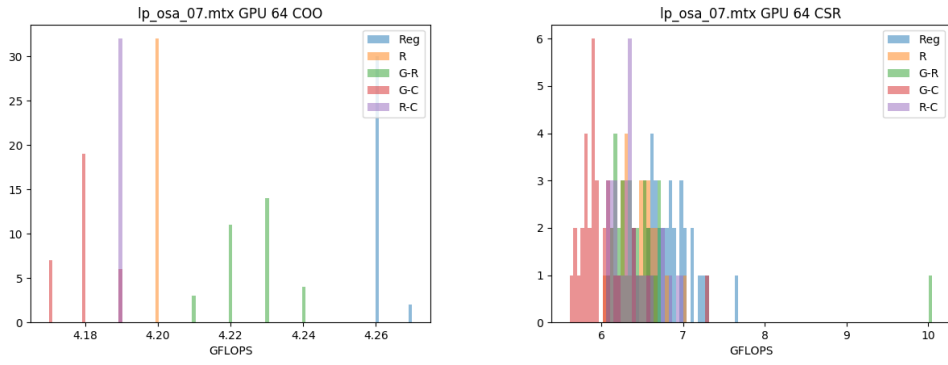


Fig. 14. Fiji, GPU 64bits COO (left) and GPU CSR (right) for OPF 3754

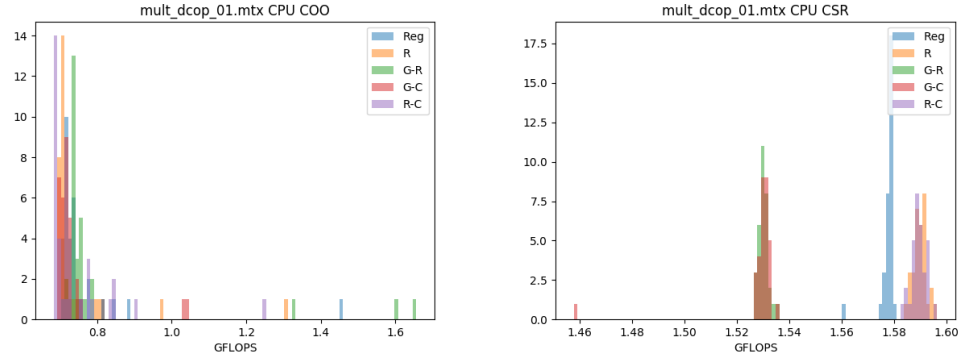


Fig. 15. CPU COO (left) and CPU CSR (right) for MULT DCOP 01

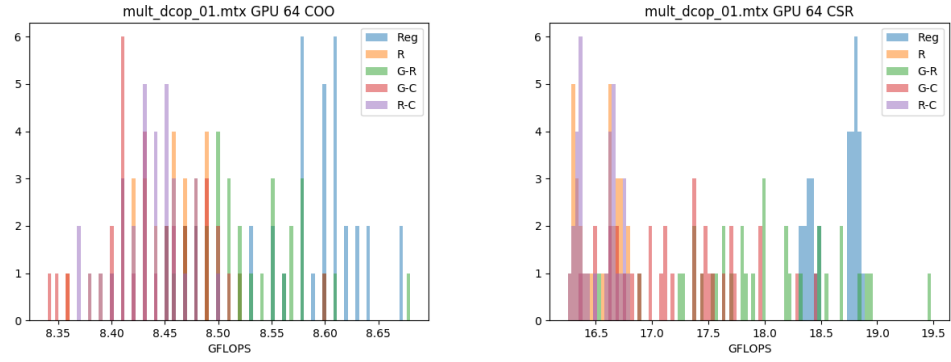


Fig. 16. Vega 20, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

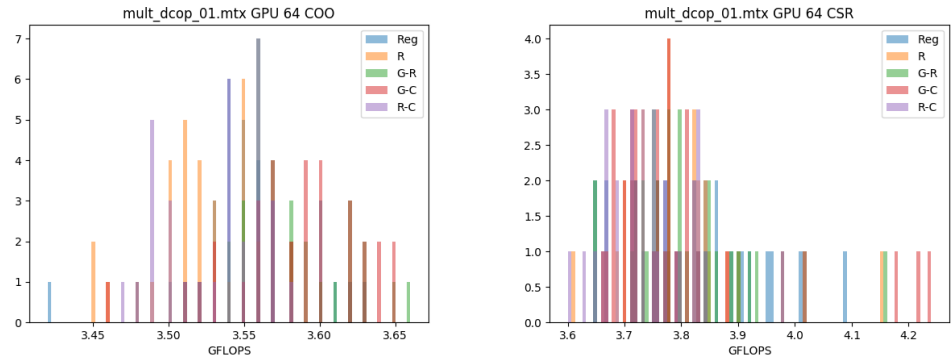


Fig. 17. Ellesmere, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

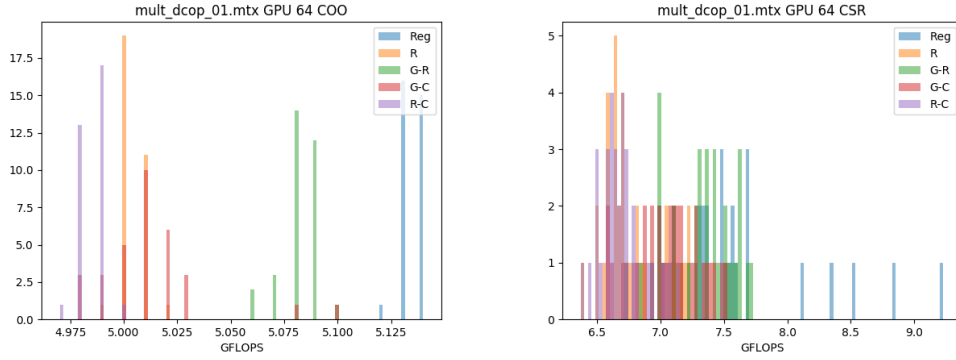


Fig. 18. Fiji, GPU 64bits COO (left) and GPU CSR (right) for MULT DCOP 01

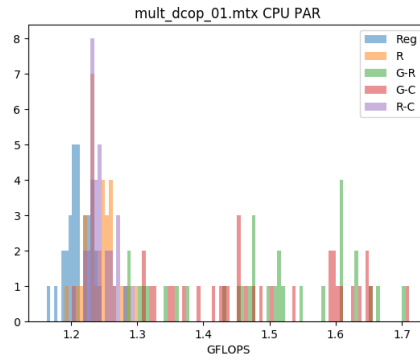


Fig. 19. Parallel CPU CSR for MULT DCOP 01

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.

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

237 7.2 Parallel CSR using up to 16 cores

238 Python provides the concept of Pool to exploit a naive parallel computation. We notice that work given to a Pool is split
 239 accordingly to the number of elements to separate HW cores. We also noticed that the work load move from a core
 240 to another, thus not ideal. Also we notice that Pool introduce a noticeable overhead: a Pool of 1, never achieves the
 241 performance of the single thread $z = A * b$. Using Pool allows us to investigate how a naive row partitioning without
 242 counting can scale up with number of cores. We tested by splitting the rows to 1–16 cores evenly (one thread per core)
 243 and we present the performance for only the best configuration. The randomization goal is to distribute the work
 244 uniformly: a balanced work distribution avoid the unfortunate case where a single core does all the work. We are
 245 pleased by the simplicity of the benchmark and we know we can do better.

246 7.3 GPU COO and CSR algorithms

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

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

258 7.4 Randomization sometimes works

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

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

265 8 EXPERIMENTAL RESULTS

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

268 Vega 20 can deliver 3.5TFLOPS in double precision and it has 1TB/s HBM memory. Each Fiji provides 0.5 TFLOPS in
 269 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 area 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 redistribute every other sample/card to different parts and these can be permuted locally.

We report in the following the performance results, 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.

9 VEGA VII AND THREADRIPPER

286	mult_dcop_03.mtx
287	Regular
288	
289	CPU COO min 0.728 max 0.880 mean 0.757
290	CPU CSR min 1.563 max 1.581 mean 1.577
291	GPU 64 COO min 8.540 max* 8.670 mean 8.619
292	CSR min 18.320 max 18.930 mean 18.620
293	CPU PAR min 1.170 max 1.269 mean 1.226
294	H min 9.689 max 9.689 mean 9.689
295	Row-Premute
296	CPU COO min 0.710 max 0.845 mean 0.724
297	CPU CSR min 1.549 max* 1.597 mean 1.589
298	GPU 64 COO min 8.360 max 8.540 mean 8.442
299	CSR min 16.260 max 16.780 mean 16.551
300	CPU PAR min 1.205 max 1.319 mean 1.263
301	H min 10.737 max 10.742 mean 10.740
302	Row-Gradient
303	CPU COO min 0.706 max 1.603 mean 0.806
304	CPU CSR min 1.493 max 1.534 mean 1.528
305	GPU 64 COO min 8.430 max 8.610 mean 8.527
306	CSR min 17.070 max*18.970 mean 18.115
307	CPU PAR min 1.331 max 1.695 mean 1.513
308	H min 10.576 max 10.585 mean 10.580
309	Column-Gradient
310	CPU COO min 0.694 max* 1.632 mean 0.797
311	CPU CSR min 1.491 max 1.534 mean 1.529
312	GPU 64 COO min 8.350 max 8.520 mean 8.429
313	CSR min 15.970 max 18.180 mean 17.124
314	CPU PAR min 1.321 max* 1.728 mean 1.514
315	H min 10.826 max*10.840 mean 10.833
316	Row-Column-Permute
317	CPU COO min 0.688 max 0.757 mean 0.696
318	CPU CSR min 1.490 max 1.595 mean 1.584
319	GPU 64 COO min 8.380 max 8.500 mean 8.445
320	CSR min 16.230 max 16.780 mean 16.513
321	CPU PAR min 1.192 max 1.274 mean 1.237
322	H min 10.737 max 10.742 mean 10.740
323	mult_dcop_01.mtx
324	Regular
325	CPU COO min 0.710 max 1.453 mean 0.761
326	CPU CSR min 1.561 max 1.581 mean 1.578
327	GPU 64 COO min 8.520 max 8.670 mean 8.597
328	CSR min 18.320 max 18.870 mean 18.636
329	CPU PAR min 1.163 max 1.246 mean 1.212
330	H min 9.689 max 9.689 mean 9.689
331	Row-Premute
332	CPU COO min 0.699 max 1.305 mean 0.745
333	CPU CSR min 1.585 max 1.597 mean 1.590
334	GPU 64 COO min 8.360 max 8.520 mean 8.446
335	CSR min 16.260 max 16.780 mean 16.528
336	CPU PAR min 1.192 max 1.298 mean 1.242
337	H min 10.738 max 10.742 mean 10.740
338	Row-Gradient
339	CPU COO min 0.709 max* 1.656 mean 0.819
340	CPU CSR min 1.527 max 1.535 mean 1.530
341	GPU 64 COO min 8.450 max* 8.680 mean 8.527
342	CSR min 16.520 max*19.480 mean 17.984
343	CPU PAR min 1.280 max 1.704 mean 1.485
344	H min 10.572 max 10.585 mean 10.581
345	Column-Gradient
346	CPU COO min 0.698 max 1.042 mean 0.737
347	CPU CSR min 1.458 max 1.536 mean 1.528
348	GPU 64 COO min 8.340 max 8.600 mean 8.443
349	CSR min 16.360 max 18.450 mean 17.247
350	CPU PAR min 1.307 max* 1.712 mean 1.494
351	H min 10.823 max*10.841 mean 10.835
352	Row-Column-Permute
353	CPU COO min 0.683 max 1.247 mean 0.749
354	CPU CSR min 1.583 max* 1.595 mean 1.590
355	GPU 64 COO min 8.370 max 8.500 mean 8.435
356	CSR min 16.250 max 16.780 mean 16.518
357	CPU PAR min 1.206 max 1.291 mean 1.243
358	H min 10.738 max 10.742 mean 10.740

359	mult_dcop_02.mtx
360	Regular
361	CPU COO min 1.615 max* 1.677 mean 1.652
362	CPU CSR min 1.539 max 1.579 mean 1.575
363	GPU 64 COO min 8.530 max* 8.700 mean 8.614
364	CSR min 18.290 max 18.890 mean 18.597
365	CPU PAR min 1.120 max 1.248 mean 1.211
366	H min 9.689 max 9.689 mean 9.689
367	Row-Premute
368	CPU COO min 0.684 max 0.780 mean 0.705
369	CPU CSR min 1.558 max* 1.596 mean 1.588
370	GPU 64 COO min 8.360 max 8.490 mean 8.433
371	CSR min 16.240 max 16.750 mean 16.552
372	CPU PAR min 1.182 max 1.277 mean 1.242
373	H min 10.737 max 10.742 mean 10.740
374	Row-Gradient
375	CPU COO min 0.704 max 1.373 mean 0.790
376	CPU CSR min 1.518 max 1.535 mean 1.529
377	GPU 64 COO min 8.420 max 8.590 mean 8.517
378	CSR min 16.680 max*19.550 mean 17.907
379	CPU PAR min 1.328 max* 1.713 mean 1.484
380	H min 10.572 max 10.585 mean 10.581
381	Column-Gradient
382	CPU COO min 0.697 max 1.460 mean 0.742
383	CPU CSR min 1.517 max 1.534 mean 1.527
384	GPU 64 COO min 8.330 max 8.490 mean 8.420
385	CSR min 16.020 max 18.390 mean 17.303
386	CPU PAR min 1.321 max 1.709 mean 1.557
387	H min 10.823 max*10.843 mean 10.835
388	Row-Column-Permute
389	CPU COO min 0.691 max 0.746 mean 0.698
390	CPU CSR min 1.568 max 1.595 mean 1.587
391	GPU 64 COO min 8.350 max 8.500 mean 8.436
392	CSR min 16.250 max 16.780 mean 16.517
393	CPU PAR min 1.187 max 1.280 mean 1.228
394	H min 10.739 max 10.743 mean 10.740
395	lp_fit2d.mtx
396	Regular
397	CPU COO min 0.774 max 0.804 mean 0.793
398	CPU CSR min 2.538 max 2.550 mean 2.547
399	GPU 64 COO min 7.060 max 7.170 mean 7.101
400	CSR min 15.650 max*18.700 mean 18.031
401	CPU PAR min 1.537 max 1.645 mean 1.590
402	H min 11.109 max 11.109 mean 11.109
403	Row-Premute
404	CPU COO min 0.740 max 0.776 mean 0.746
405	CPU CSR min 3.302 max* 3.328 mean 3.317
406	GPU 64 COO min 7.040 max* 7.180 mean 7.098
407	CSR min 15.690 max 18.580 mean 16.732
408	CPU PAR min 1.327 max 1.482 mean 1.422
409	H min 11.098 max 11.105 mean 11.101
410	Row-Gradient
411	CPU COO min 0.739 max* 2.092 mean 1.091
412	CPU CSR min 2.539 max 2.546 mean 2.543
413	GPU 64 COO min 7.040 max 7.150 mean 7.100
414	CSR min 15.520 max 18.560 mean 17.547
415	CPU PAR min 1.401 max 1.661 mean 1.525
416	H min 11.109 max 11.109 mean 11.109
417	Column-Gradient
418	CPU COO min 0.726 max 2.065 mean 1.011
419	CPU CSR min 2.539 max 2.550 mean 2.546
420	GPU 64 COO min 6.800 max 7.140 mean 7.080
421	CSR min 15.480 max 18.560 mean 16.866
422	CPU PAR min 1.391 max* 1.737 mean 1.563
423	H min 11.329 max 11.333 mean 11.331
424	Row-Column-Permute
425	CPU COO min 0.746 max 0.782 mean 0.754
426	CPU CSR min 3.310 max 3.324 mean 3.318
427	GPU 64 COO min 7.030 max 7.160 mean 7.100
428	CSR min 15.730 max 18.530 mean 17.362
429	CPU PAR min 1.340 max 1.451 mean 1.401
430	H min 11.099 max 11.104 mean 11.102
431	bloweya.mtx
432	Regular

433		CPU COO	min	0.727	max*	1.815	mean	0.892	507		GPU 64 COO	min	11.340	max*	11.860	mean	11.441
434		CPU CSR	min	2.867	max*	2.936	mean	2.917	508		CSR	min	36.010	max*	40.960	mean	38.048
435		GPU 64 COO	min	0.000	max	0.000	mean	0.000	509		CPU PAR	min	2.019	max	2.204	mean	2.130
436		CSR	min	0.000	max	0.000	mean	0.000	510		H	min	8.228	max	8.228	mean	8.228
437		CPU PAR	min	1.680	max*	1.751	mean	1.719	511	Row-Premute							
438		H	min	7.205	max	7.205	mean	7.205	512		CPU COO	min	0.718	max	0.751	mean	0.732
439	Row-Premute								513		CPU CSR	min	2.488	max	2.507	mean	2.498
440		CPU COO	min	0.678	max	1.483	mean	0.746	514		GPU 64 COO	min	10.810	max	11.090	mean	10.949
441		CPU CSR	min	2.311	max	2.326	mean	2.320	515		CSR	min	24.860	max	26.410	mean	25.527
442		GPU 64 COO	min	6.840	max*	7.270	mean	6.930	516		CPU PAR	min	1.978	max	2.290	mean	2.135
443		CSR	min	15.650	max	16.800	mean	16.233	517		H	min	11.836	max	11.840	mean	11.838
444		CPU PAR	min	1.649	max	1.730	mean	1.682	518	Row-Gradient							
445		H	min	11.026	max	11.031	mean	11.029	519		CPU COO	min	0.722	max	1.794	mean	0.769
446	Row-Gradient								520		CPU CSR	min	2.407	max	2.421	mean	2.416
447		CPU COO	min	0.708	max	1.209	mean	0.779	521		GPU 64 COO	min	11.210	max	11.480	mean	11.317
448		CPU CSR	min	1.648	max	1.735	mean	1.709	522		CSR	min	31.920	max	34.690	mean	33.246
449		GPU 64 COO	min	6.920	max	7.080	mean	7.015	523		CPU PAR	min	2.184	max*	2.302	mean	2.232
450		CSR	min	16.950	max	19.500	mean	17.794	524		H	min	10.742	max	10.757	mean	10.748
451		CPU PAR	min	1.497	max	1.743	mean	1.608	525	Column-Gradient							
452		H	min	10.298	max	10.304	mean	10.301	526		CPU COO	min	0.720	max	0.916	mean	0.742
453	Column-Gradient								527		CPU CSR	min	2.395	max	2.410	mean	2.402
454		CPU COO	min	0.709	max	1.536	mean	0.817	528		GPU 64 COO	min	10.840	max	11.070	mean	10.946
455		CPU CSR	min	1.705	max	1.753	mean	1.735	529		CSR	min	24.340	max	26.140	mean	25.393
456		GPU 64 COO	min	6.800	max	7.120	mean	6.865	530		CPU PAR	min	2.184	max	2.272	mean	2.223
457		CSR	min	15.480	max*	17.710	mean	16.470	531		H	min	11.873	max	11.882	mean	11.878
458		CPU PAR	min	1.446	max	1.718	mean	1.591	532	Row-Column-Permute							
459		H	min	10.880	max	10.886	mean	10.883	533		CPU COO	min	0.707	max	0.748	mean	0.714
460	Row-Column-Permute								534		CPU CSR	min	2.458	max	2.511	mean	2.506
461		CPU COO	min	0.670	max	1.024	mean	0.706	535		GPU 64 COO	min	10.880	max	11.070	mean	10.957
462		CPU CSR	min	2.199	max	2.340	mean	2.326	536		CSR	min	24.890	max	26.490	mean	25.642
463		GPU 64 COO	min	6.800	max	6.980	mean	6.933	537		CPU PAR	min	2.209	max	2.282	mean	2.240
464		CSR	min	15.610	max	16.900	mean	16.227	538		H	min	11.834	max*	11.840	mean	11.838
465		CPU PAR	min	1.598	max	1.668	mean	1.632	539	brainpc2.mtx							
466		H	min	11.025	max*	11.032	mean	11.029	540	Regular							
467	lp_osa_07.mtx								541		CPU COO	min	0.732	max	0.751	mean	0.744
468	Regular								542		CPU CSR	min	2.885	max*	2.916	mean	2.909
469		CPU COO	min	0.715	max	1.798	mean	0.885	543		GPU 64 COO	min	0.000	max	0.000	mean	0.000
470		CPU CSR	min	2.495	max	2.551	mean	2.547	544		CSR	min	0.000	max	0.000	mean	0.000
471		GPU 64 COO	min	7.650	max*	7.790	mean	7.718	545		CPU PAR	min	1.276	max	1.299	mean	1.286
472		CSR	min	16.390	max*	18.350	mean	17.093	546		H	min	7.478	max	7.478	mean	7.478
473		CPU PAR	min	0.963	max	1.012	mean	0.995	547	Row-Premute							
474		H	min	8.412	max	8.412	mean	8.412	548		CPU COO	min	0.727	max	0.855	mean	0.736
475	Row-Premute								549		CPU CSR	min	2.385	max	2.411	mean	2.397
476		CPU COO	min	0.720	max*	2.078	mean	1.104	550		GPU 64 COO	min	8.120	max	8.410	mean	8.206
477		CPU CSR	min	2.656	max*	2.679	mean	2.669	551		CSR	min	18.670	max	19.960	mean	19.536
478		GPU 64 COO	min	7.610	max	7.690	mean	7.647	552		CPU PAR	min	1.293	max	1.340	mean	1.314
479		CSR	min	15.910	max	17.210	mean	16.750	553		H	min	9.809	max	9.813	mean	9.811
480		CPU PAR	min	0.890	max	0.940	mean	0.918	554	Row-Gradient							
481		H	min	9.255	max	9.258	mean	9.256	555		CPU COO	min	0.696	max*	1.546	mean	0.785
482	Row-Gradient								556		CPU CSR	min	1.361	max	1.420	mean	1.411
483		CPU COO	min	0.725	max	2.078	mean	1.041	557		GPU 64 COO	min	8.190	max*	8.550	mean	8.302
484		CPU CSR	min	2.487	max	2.502	mean	2.495	558		CSR	min	18.700	max*	21.000	mean	19.890
485		GPU 64 COO	min	7.570	max	7.730	mean	7.655	559		CPU PAR	min	1.435	max	1.666	mean	1.549
486		CSR	min	15.370	max	18.100	mean	16.803	560		H	min	9.721	max	9.727	mean	9.723
487		CPU PAR	min	1.435	max	1.796	mean	1.592	561	Column-Gradient							
488		H	min	8.637	max	8.678	mean	8.672	562		CPU COO	min	0.698	max	1.467	mean	0.746
489	Column-Gradient								563		CPU CSR	min	1.377	max	1.423	mean	1.414
490		CPU COO	min	0.724	max	1.990	mean	1.000	564		GPU 64 COO	min	8.110	max	8.290	mean	8.187
491		CPU CSR	min	2.425	max	2.477	mean	2.448	565		CSR	min	18.090	max	20.190	mean	19.217
492		GPU 64 COO	min	7.510	max	7.660	mean	7.596	566		CPU PAR	min	1.345	max*	1.681	mean	1.518
493		CSR	min	14.410	max	16.290	mean	15.267	567		H	min	10.369	max*	10.372	mean	10.370
494		CPU PAR	min	1.238	max	1.774	mean	1.534	568	Row-Column-Permute							
495		H	min	9.447	max*	9.603	mean	9.576	569		CPU COO	min	0.698	max	1.390	mean	0.788
496	Row-Column-Permute								570		CPU CSR	min	2.387	max	2.410	mean	2.399
497		CPU COO	min	0.738	max	1.950	mean	1.071	571		GPU 64 COO	min	8.120	max	8.260	mean	8.191
498		CPU CSR	min	2.522	max	2.709	mean	2.675	572		CSR	min	18.530	max	19.960	mean	19.307
499		GPU 64 COO	min	7.600	max	7.690	mean	7.641	573		CPU PAR	min	1.295	max	1.347	mean	1.319
500		CSR	min	15.820	max	17.190	mean	16.572	574		H	min	9.809	max	9.813	mean	9.811
501		CPU PAR	min	0.891	max	0.944	mean	0.924	575	shermanACb.mtx							
502		H	min	9.255	max	9.258	mean	9.256	576	Regular							
503	ex19.mtx								577		CPU COO	min	0.712	max	1.201	mean	0.756
504	Regular								578		CPU CSR	min	1.558	max	1.601	mean	1.596
505		CPU COO	min	0.732	max*	1.837	mean	1.076	579		GPU 64 COO	min	7.080	max*	7.370	mean	7.184
506		CPU CSR	min	2.563	max*	2.586	mean	2.577	580		CSR	min	17.580	max*	19.480	mean	18.770

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729		CPU CSR	min	2.358	max	2.413	mean	2.392	803		CSR	min	19.960	max	21.190	mean	20.696
730		GPU 64 COO	min	11.430	max	11.770	mean	11.549	804		CPU PAR	min	1.303	max	1.371	mean	1.345
731		CSR	min	24.470	max	25.580	mean	24.785	805		H	min	10.059	max	10.062	mean	10.061
732		CPU PAR	min	1.758	max	1.896	mean	1.829	806	Row-Gradient							
733		H	min	11.872	max	11.877	mean	11.875	807		CPU COO	min	0.723	max	0.984	mean	0.753
734	Row-Gradient								808		CPU CSR	min	1.781	max	1.809	mean	1.803
735		CPU COO	min	0.716	max	0.775	mean	0.739	809		GPU 64 COO	min	9.380	max	9.660	mean	9.464
736		CPU CSR	min	1.651	max	1.689	mean	1.675	810		CSR	min	15.770	max	19.090	mean	18.037
737		GPU 64 COO	min	12.100	max	12.410	mean	12.205	811		CPU PAR	min	1.775	max	1.924	mean	1.868
738		CSR	min	31.670	max	34.910	mean	33.370	812	Column-Gradient	H	min	10.205	max	10.233	mean	10.219
739		CPU PAR	min	2.079	max	2.286	mean	2.207	813								
740		H	min	11.111	max	11.116	mean	11.113	814		CPU COO	min	0.715	max	0.926	mean	0.757
741	Column-Gradient								815		CPU CSR	min	1.729	max	1.802	mean	1.791
742		CPU COO	min	0.715	max	1.021	mean	0.743	816		GPU 64 COO	min	9.080	max	9.270	mean	9.158
743		CPU CSR	min	1.655	max	1.674	mean	1.666	817		CSR	min	13.980	max	15.780	mean	14.938
744		GPU 64 COO	min	11.340	max	11.560	mean	11.463	818		CPU PAR	min	1.751	max	1.906	mean	1.846
745		CSR	min	23.770	max	25.470	mean	24.489	819		H	min	11.213	max	11.232	mean	11.222
746		CPU PAR	min	2.056	max	2.172	mean	2.118	820	Row-Column-Permute							
747		H	min	12.040	max	12.047	mean	12.043	821		CPU COO	min	0.732	max	1.598	mean	0.785
748	Row-Column-Permute								822		CPU CSR	min	2.594	max	2.602	mean	2.599
749		CPU COO	min	0.677	max	0.785	mean	0.687	823		GPU 64 COO	min	9.340	max	9.460	mean	9.394
750		CPU CSR	min	2.325	max	2.434	mean	2.369	824		CSR	min	19.950	max	21.500	mean	20.544
751		GPU 64 COO	min	11.450	max	11.650	mean	11.538	825		CPU PAR	min	1.326	max	1.374	mean	1.354
752		CSR	min	24.330	max	25.560	mean	25.008	826		H	min	10.059	max	10.062	mean	10.061
753		CPU PAR	min	1.631	max	1.776	mean	1.709	827	mhd4800a.mtx							
754		H	min	11.873	max	11.877	mean	11.875	828	Regular							
755	OPF_3754.mtx								829		CPU COO	min	0.759	max	0.795	mean	0.780
756	Regular								830		CPU CSR	min	2.479	max	2.565	mean	2.557
757		CPU COO	min	0.726	max	0.774	mean	0.747	831		GPU 64 COO	min	5.490	max	5.650	mean	5.552
758		CPU CSR	min	2.898	max	2.919	mean	2.908	832		CSR	min	16.700	max	19.460	mean	18.004
759		GPU 64 COO	min	7.600	max	7.820	mean	7.766	833		CPU PAR	min	1.456	max	1.523	mean	1.492
760		CSR	min	25.070	max	29.030	mean	26.756	834		H	min	7.132	max	7.132	mean	7.132
761		CPU PAR	min	1.437	max	1.508	mean	1.471	835	Row-Premute							
762		H	min	8.393	max	8.393	mean	8.393	836		CPU COO	min	0.695	max	0.943	mean	0.726
763	Row-Premute								837		CPU CSR	min	2.480	max	2.488	mean	2.485
764		CPU COO	min	0.714	max	1.574	mean	0.817	838		GPU 64 COO	min	5.410	max	5.490	mean	5.453
765		CPU CSR	min	2.686	max	2.711	mean	2.699	839		CSR	min	15.700	max	17.520	mean	16.678
766		GPU 64 COO	min	7.410	max	7.570	mean	7.484	840		CPU PAR	min	1.422	max	1.514	mean	1.474
767		CSR	min	19.600	max	21.190	mean	20.307	841		H	min	10.959	max	10.966	mean	10.963
768		CPU PAR	min	1.443	max	1.505	mean	1.469	842	Row-Gradient							
769		H	min	11.267	max	11.272	mean	11.269	843		CPU COO	min	0.723	max	2.029	mean	0.990
770	Row-Gradient								844		CPU CSR	min	2.411	max	2.427	mean	2.421
771		CPU COO	min	0.723	max	1.232	mean	0.775	845		GPU 64 COO	min	5.490	max	5.560	mean	5.534
772		CPU CSR	min	1.672	max	1.691	mean	1.685	846		CSR	min	16.350	max	19.560	mean	17.784
773		GPU 64 COO	min	7.600	max	7.760	mean	7.716	847		CPU PAR	min	1.441	max	1.509	mean	1.477
774		CSR	min	23.160	max	25.590	mean	24.304	848		H	min	9.512	max	9.526	mean	9.520
775		CPU PAR	min	1.675	max	1.736	mean	1.703	849	Column-Gradient							
776		H	min	10.463	max	10.472	mean	10.468	850		CPU COO	min	0.721	max	1.802	mean	0.871
777	Column-Gradient								851		CPU CSR	min	2.393	max	2.408	mean	2.404
778		CPU COO	min	0.726	max	1.431	mean	0.778	852		GPU 64 COO	min	5.410	max	5.480	mean	5.453
779		CPU CSR	min	1.671	max	1.685	mean	1.679	853		CSR	min	15.680	max	17.870	mean	16.540
780		GPU 64 COO	min	7.410	max	7.530	mean	7.467	854		CPU PAR	min	1.429	max	1.488	mean	1.468
781		CSR	min	18.140	max	20.350	mean	19.315	855		H	min	10.931	max	10.945	mean	10.938
782		CPU PAR	min	1.650	max	1.736	mean	1.699	856	Row-Column-Permute							
783		H	min	11.393	max	11.401	mean	11.397	857		CPU COO	min	0.728	max	1.646	mean	1.037
784	Row-Column-Permute								858		CPU CSR	min	2.472	max	2.488	mean	2.480
785		CPU COO	min	0.711	max	1.458	mean	0.751	859		GPU 64 COO	min	5.410	max	5.480	mean	5.449
786		CPU CSR	min	2.678	max	2.717	mean	2.700	860		CSR	min	15.760	max	17.560	mean	16.654
787		GPU 64 COO	min	7.400	max	7.540	mean	7.471	861		CPU PAR	min	1.428	max	1.513	mean	1.474
788		CSR	min	19.560	max	21.150	mean	20.453	862		H	min	10.959	max	10.967	mean	10.963
789		CPU PAR	min	1.440	max	1.499	mean	1.467	863	gen4.mtx							
790		H	min	11.266	max	11.272	mean	11.269	864	Regular							
791	c-47.mtx								865		CPU COO	min	0.737	max	1.977	mean	1.431
792	Regular								866		CPU CSR	min	2.674	max	2.688	mean	2.681
793		CPU COO	min	0.754	max	1.829	mean	1.204	867		GPU 64 COO	min	5.900	max	6.000	mean	5.954
794		CPU CSR	min	2.610	max	2.624	mean	2.618	868		CSR	min	13.650	max	15.410	mean	14.657
795		GPU 64 COO	min	9.530	max	9.870	mean	9.640	869		CPU PAR	min	1.468	max	1.521	mean	1.491
796		CSR	min	23.990	max	25.910	mean	24.992	870		H	min	9.234	max	9.234	mean	9.234
797		CPU PAR	min	1.311	max	1.380	mean	1.357	871	Row-Premute							
798		H	min	8.364	max	8.364	mean	8.364	872		CPU COO	min	0.740	max	2.048	mean	1.121
799	Row-Premute								873		CPU CSR	min	2.777	max	2.798	mean	2.790
800		CPU COO	min	0.740	max	0.885	mean	0.755	874		GPU 64 COO	min	5.910	max	5.970	mean	5.944
801		CPU CSR	min	2.574	max	2.611	mean	2.597	875		CSR	min	13.700	max	15.370	mean	14.541
802		GPU 64 COO	min	9.320	max	9.510	mean	9.397	876		CPU PAR	min	1.468	max	1.546	mean	1.502

877		H	min 10.250 max 10.255 mean 10.252	951	CPU COO	min 0.735 max 1.806 mean 0.878
878	Row-Gradient			952	CPU CSR	min 2.706 max 2.744 mean 2.726
879		CPU COO	min 0.740 max 1.790 mean 0.994	953	GPU 64 COO	min 6.390 max 6.500 mean 6.433
880		CPU CSR	min 2.663 max 2.682 mean 2.674	954	CSR	min 19.780 max 22.870 mean 20.936
881		GPU 64 COO	min 5.890 max* 6.160 mean 5.946	955	CPU PAR	min 1.710 max 1.865 mean 1.785
882		CSR	min 13.780 max*17.520 mean 15.601	956	H	min 10.251 max 10.267 mean 10.257
883		CPU PAR	min 1.479 max* 1.619 mean 1.569	957	Column-Gradient	
884		H	min 9.939 max 9.955 mean 9.948	958		CPU COO min 0.728 max 1.792 mean 0.986
885	Column-Gradient			959	CPU CSR	min 2.521 max 2.720 mean 2.703
886		CPU COO	min 0.743 max 1.991 mean 0.981	960	GPU 64 COO	min 6.280 max 6.370 mean 6.327
887		CPU CSR	min 2.620 max 2.654 mean 2.646	961	CSR	min 18.000 max 19.720 mean 19.040
888		GPU 64 COO	min 5.840 max 5.910 mean 5.885	962	CPU PAR	min 1.649 max 1.741 mean 1.702
889		CSR	min 13.130 max 17.040 mean 15.008	963	H	min 11.113 max 11.121 mean 11.117
890		CPU PAR	min 1.477 max 1.607 mean 1.559	964	Row-Column-Permute	
891		H	min 10.858 max*10.876 mean 10.864	965		CPU COO min 0.714 max 1.525 mean 0.957
892	Row-Column-Permute			966	CPU CSR	min 2.876 max 2.892 mean 2.884
893		CPU COO	min 0.742 max 2.010 mean 1.124	967	GPU 64 COO	min 6.280 max 6.370 mean 6.322
894		CPU CSR	min 2.789 max* 2.800 mean 2.795	968	CSR	min 17.960 max 19.670 mean 18.670
895		GPU 64 COO	min 5.900 max 5.980 mean 5.941	969	CPU PAR	min 1.667 max 1.754 mean 1.710
896		CSR	min 13.640 max 15.410 mean 14.556	970	H	min 11.162 max*11.168 mean 11.165
897		CPU PAR	min 1.462 max 1.540 mean 1.504	971	TSOPF_RS_b39_c7.mtx	
898		H	min 10.250 max 10.253 mean 10.252	972	Regular	
899	Maragal_6.mtx			973	CPU COO	min 0.771 max 0.793 mean 0.780
900	Regular			974	CPU CSR	min 3.219 max* 3.232 mean 3.227
901		CPU COO	min 0.725 max 0.741 mean 0.729	975	GPU 64 COO	min 11.070 max*11.200 mean 11.142
902		CPU CSR	min 2.345 max 2.409 mean 2.372	976	CSR	min 37.050 max*42.100 mean 39.040
903		GPU 64 COO	min 18.200 max 18.770 mean 18.357	977	CPU PAR	min 1.910 max 2.027 mean 1.982
904		CSR	min 38.310 max*40.240 mean 39.477	978	H	min 7.304 max 7.304 mean 7.304
905		CPU PAR	min 0.789 max 0.813 mean 0.797	979	Row-Premute	
906		H	min 9.930 max 9.930 mean 9.930	980		CPU COO min 0.701 max 0.722 mean 0.707
907	Row-Premute			981	CPU CSR	min 2.931 max 2.952 mean 2.942
908		CPU COO	min 0.709 max 0.779 mean 0.715	982	GPU 64 COO	min 10.860 max 11.030 mean 10.928
909		CPU CSR	min 2.675 max 2.715 mean 2.696	983	CSR	min 28.730 max 30.880 mean 29.483
910		GPU 64 COO	min 17.810 max 18.030 mean 17.935	984	CPU PAR	min 1.760 max 1.922 mean 1.851
911		CSR	min 29.650 max 30.580 mean 30.109	985	H	min 10.537 max 10.541 mean 10.539
912		CPU PAR	min 0.857 max 0.940 mean 0.904	986	Row-Gradient	
913		H	min 10.777 max 10.779 mean 10.778	987		CPU COO min 0.747 max 0.808 mean 0.757
914	Row-Gradient			988	CPU CSR	min 2.606 max 2.648 mean 2.624
915		CPU COO	min 0.710 max* 1.566 mean 0.755	989	GPU 64 COO	min 10.850 max 11.120 mean 10.999
916		CPU CSR	min 2.042 max 2.159 mean 2.120	990	CSR	min 33.910 max 37.600 mean 35.909
917		GPU 64 COO	min 18.460 max*18.960 mean 18.665	991	CPU PAR	min 2.154 max* 2.245 mean 2.203
918		CSR	min 25.650 max 27.330 mean 26.549	992	H	min 9.636 max 9.646 mean 9.642
919		CPU PAR	min 2.257 max 2.612 mean 2.416	993	Column-Gradient	
920		H	min 11.251 max 11.301 mean 11.285	994		CPU COO min 0.718 max* 1.693 mean 0.802
921	Column-Gradient			995	CPU CSR	min 2.502 max 2.585 mean 2.547
922		CPU COO	min 0.711 max 0.743 mean 0.725	996	GPU 64 COO	min 10.700 max 10.990 mean 10.804
923		CPU CSR	min 2.036 max 2.161 mean 2.110	997	CSR	min 27.230 max 29.380 mean 28.488
924		GPU 64 COO	min 17.840 max 18.860 mean 18.149	998	CPU PAR	min 2.128 max 2.227 mean 2.172
925		CSR	min 19.410 max 20.690 mean 20.066	999	H	min 11.131 max*11.222 mean 11.208
926		CPU PAR	min 2.174 max* 2.546 mean 2.349	1000	Row-Column-Permute	
927		H	min 12.011 max*12.072 mean 12.052	1001		CPU COO min 0.709 max 0.726 mean 0.716
928	Row-Column-Permute			1002	CPU CSR	min 2.917 max 2.958 mean 2.940
929		CPU COO	min 0.712 max 0.971 mean 0.737	1003	GPU 64 COO	min 10.840 max 11.030 mean 10.930
930		CPU CSR	min 2.732 max* 2.751 mean 2.743	1004	CSR	min 28.780 max 30.810 mean 29.578
931		GPU 64 COO	min 17.720 max 18.070 mean 17.911	1005	CPU PAR	min 1.757 max 1.834 mean 1.792
932		CSR	min 29.600 max 30.500 mean 29.961	1006	H	min 10.537 max 10.540 mean 10.539
933		CPU PAR	min 0.827 max 0.954 mean 0.913			
934		H	min 10.776 max 10.778 mean 10.777			
935	aft01.mtx			1007	10 ELLESMERE	
936	Regular			1008	aft01.mtx	
937		CPU COO	min 0.735 max* 2.079 mean 1.069	1009	Regular	
938		CPU CSR	min 3.132 max* 3.154 mean 3.145	1010	GPU 64 COO	min 4.080 max* 4.280 mean 4.186
939		GPU 64 COO	min 6.390 max* 6.610 mean 6.457	1011	CSR	min 9.660 max*12.660 mean 11.485
940		CSR	min 19.990 max*23.250 mean 21.820	1012	H	min 7.811 max 7.811 mean 7.811
941		CPU PAR	min 1.746 max* 1.865 mean 1.812	1013	Row-Premute	
942		H	min 7.811 max 7.811 mean 7.811	1014		GPU 64 COO min 3.860 max 4.090 mean 4.001
943	Row-Premute			1015	CSR	min 9.520 max 10.340 mean 9.936
944		CPU COO	min 0.714 max 1.648 mean 0.840	1016	H	min 11.161 max 11.167 mean 11.165
945		CPU CSR	min 2.864 max 2.892 mean 2.883	1017	Row-Gradient	
946		GPU 64 COO	min 6.280 max 6.380 mean 6.329	1018		GPU 64 COO min 4.010 max 4.240 mean 4.135
947		CSR	min 17.980 max 19.700 mean 19.105	1019	CSR	min 5.890 max 11.350 mean 6.882
948		CPU PAR	min 1.729 max 1.850 mean 1.782	1020	H	min 10.246 max 10.262 mean 10.256
949		H	min 11.162 max 11.168 mean 11.165	1021	Column-Gradient	
950	Row-Gradient					

1022		GPU 64 COO min 3.850 max 4.100 mean 4.012	1096		H min 7.380 max 7.380 mean 7.380
1023		CSR min 5.460 max 8.790 mean 6.005	1097	Row-Premute	
1024		H min 11.112 max 11.122 mean 11.117	1098		GPU 64 COO min 4.820 max 4.940 mean 4.859
1025	Row-Column-Permute		1099		CSR min 5.080 max 6.520 mean 6.342
1026		GPU 64 COO min 3.850 max 4.080 mean 3.990	1100		H min 10.042 max 10.047 mean 10.044
1027		CSR min 5.420 max 6.760 mean 5.977	1101	Row-Gradient	
1028		H min 11.162 max*11.169 mean 11.165	1102		GPU 64 COO min 4.810 max* 4.940 mean 4.876
1029	bloweya.mtx		1103		CSR min 6.100 max* 6.560 mean 6.307
1030	Regular		1104		H min 9.681 max 9.704 mean 9.694
1031		GPU 64 COO min 0.000 max 0.000 mean 0.000	1105	Column-Gradient	
1032		CSR min 0.000 max 0.000 mean 0.000	1106		GPU 64 COO min 4.810 max 4.930 mean 4.869
1033		H min 7.205 max 7.205 mean 7.205	1107		CSR min 4.820 max 6.460 mean 6.208
1034	Row-Premute		1108		H min 10.554 max*10.661 mean 10.638
1035		GPU 64 COO min 3.800 max 3.940 mean 3.875	1109	Row-Column-Permute	
1036		CSR min 3.710 max 4.570 mean 4.399	1110		GPU 64 COO min 4.810 max 4.940 mean 4.864
1037		H min 11.025 max 11.031 mean 11.028	1111		CSR min 5.930 max 6.520 mean 6.379
1038	Row-Gradient		1112		H min 10.041 max 10.047 mean 10.044
1039		GPU 64 COO min 3.800 max* 4.120 mean 3.962	1113	cvxqp3.mtx	
1040		CSR min 4.340 max* 4.670 mean 4.546	1114	Regular	
1041		H min 10.296 max 10.307 mean 10.300	1115		GPU 64 COO min 3.350 max* 3.590 mean 3.483
1042	Column-Gradient		1116		CSR min 5.430 max* 9.260 mean 8.333
1043		GPU 64 COO min 3.880 max 4.100 mean 3.978	1117		H min 8.646 max 8.646 mean 8.646
1044		CSR min 4.240 max 4.570 mean 4.412	1118	Row-Premute	
1045		H min 10.881 max 10.886 mean 10.883	1119		GPU 64 COO min 3.230 max 3.480 mean 3.371
1046	Row-Column-Permute		1120		CSR min 7.560 max 8.220 mean 7.900
1047		GPU 64 COO min 3.800 max 3.980 mean 3.885	1121		H min 11.027 max 11.033 mean 11.030
1048		CSR min 4.130 max 4.540 mean 4.399	1122	Row-Gradient	
1049		H min 11.025 max*11.033 mean 11.029	1123		GPU 64 COO min 3.240 max 3.510 mean 3.396
1050	brainpc2.mtx		1124		CSR min 6.990 max 7.890 mean 7.574
1051	Regular		1125		H min 11.060 max 11.069 mean 11.064
1052		GPU 64 COO min 0.000 max 0.000 mean 0.000	1126	Column-Gradient	
1053		CSR min 0.000 max 0.000 mean 0.000	1127		GPU 64 COO min 3.240 max 3.480 mean 3.374
1054		H min 7.478 max 7.478 mean 7.478	1128		CSR min 6.980 max 7.900 mean 7.557
1055	Row-Premute		1129		H min 11.126 max*11.134 mean 11.130
1056		GPU 64 COO min 3.840 max* 6.750 mean 4.110	1130	Row-Column-Permute	
1057		CSR min 4.260 max* 4.500 mean 4.437	1131		GPU 64 COO min 3.110 max 3.470 mean 3.365
1058		H min 9.809 max 9.813 mean 9.811	1132		CSR min 4.810 max 8.210 mean 7.742
1059	Row-Gradient		1133		H min 11.026 max 11.032 mean 11.030
1060		GPU 64 COO min 0.640 max 4.030 mean 3.864	1134	ex19.mtx	
1061		CSR min 4.270 max 4.470 mean 4.383	1135	Regular	
1062		H min 9.722 max 9.727 mean 9.724	1136		GPU 64 COO min 2.450 max* 2.610 mean 2.564
1063	Column-Gradient		1137		CSR min 4.490 max 4.760 mean 4.714
1064		GPU 64 COO min 0.640 max 4.070 mean 3.898	1138		H min 8.228 max 8.228 mean 8.228
1065		CSR min 4.230 max 4.500 mean 4.386	1139	Row-Premute	
1066		H min 10.368 max*10.372 mean 10.370	1140		GPU 64 COO min 2.000 max 2.040 mean 2.021
1067	Row-Column-Permute		1141		CSR min 4.640 max 4.780 mean 4.733
1068		GPU 64 COO min 3.980 max 4.110 mean 4.027	1142		H min 11.835 max 11.840 mean 11.838
1069		CSR min 4.320 max 4.490 mean 4.437	1143	Row-Gradient	
1070		H min 9.809 max 9.813 mean 9.811	1144		GPU 64 COO min 2.240 max 2.390 mean 2.329
1071	c-47.mtx		1145		CSR min 4.570 max* 4.850 mean 4.807
1072	Regular		1146		H min 10.742 max 10.752 mean 10.747
1073		GPU 64 COO min 3.980 max* 4.080 mean 4.026	1147	Column-Gradient	
1074		CSR min 4.760 max 4.850 mean 4.812	1148		GPU 64 COO min 2.010 max 2.050 mean 2.034
1075		H min 8.364 max 8.364 mean 8.364	1149		CSR min 4.570 max 4.760 mean 4.701
1076	Row-Premute		1150		H min 11.872 max*11.881 mean 11.878
1077		GPU 64 COO min 3.880 max 4.010 mean 3.942	1151	Row-Column-Permute	
1078		CSR min 4.040 max 4.900 mean 4.807	1152		GPU 64 COO min 2.000 max 2.040 mean 2.023
1079		H min 10.059 max 10.063 mean 10.061	1153		CSR min 0.770 max 4.780 mean 4.594
1080	Row-Gradient		1154		H min 11.835 max 11.840 mean 11.838
1081		GPU 64 COO min 3.900 max 4.050 mean 3.976	1155	gen4.mtx	
1082		CSR min 4.380 max 4.740 mean 4.630	1156	Regular	
1083		H min 10.201 max 10.228 mean 10.214	1157		GPU 64 COO min 4.880 max 4.980 mean 4.900
1084	Column-Gradient		1158		CSR min 10.020 max*11.300 mean 10.716
1085		GPU 64 COO min 3.860 max 3.990 mean 3.936	1159		H min 9.234 max 9.234 mean 9.234
1086		CSR min 4.350 max 4.610 mean 4.525	1160	Row-Premute	
1087		H min 11.204 max*11.241 mean 11.222	1161		GPU 64 COO min 4.860 max 4.930 mean 4.890
1088	Row-Column-Permute		1162		CSR min 0.330 max 11.200 mean 10.038
1089		GPU 64 COO min 3.890 max 4.020 mean 3.953	1163		H min 10.249 max 10.254 mean 10.252
1090		CSR min 4.490 max* 4.920 mean 4.840	1164	Row-Gradient	
1091		H min 10.058 max 10.063 mean 10.061	1165		GPU 64 COO min 4.860 max* 4.990 mean 4.908
1092	case9.mtx		1166		CSR min 9.160 max 11.240 mean 10.435
1093	Regular		1167		H min 9.939 max 9.961 mean 9.947
1094		GPU 64 COO min 0.000 max 0.000 mean 0.000	1168	Column-Gradient	
1095		CSR min 0.000 max 0.000 mean 0.000	1169		GPU 64 COO min 4.780 max 4.880 mean 4.816

1170		CSR min 7.770 max 10.570 mean 9.407	1244	Row-Permute	
1171		H min 10.851 max*10.876 mean 10.864	1245		GPU 64 COO min 4.420 max 4.520 mean 4.445
1172	Row-Column-Permute		1246		CSR min 10.520 max 10.880 mean 10.696
1173		GPU 64 COO min 4.850 max 4.950 mean 4.886	1247		H min 10.960 max*10.968 mean 10.963
1174		CSR min 10.220 max 11.280 mean 10.748	1248	Row-Gradient	
1175		H min 10.250 max 10.255 mean 10.252	1249		GPU 64 COO min 4.570 max 4.690 mean 4.605
1176	lp_fit2d.mtx		1250		CSR min 4.550 max 13.350 mean 12.479
1177	Regular		1251		H min 9.508 max 9.527 mean 9.520
1178		GPU 64 COO min 4.360 max* 4.640 mean 4.515	1252	Column-Gradient	
1179		CSR min 10.080 max 10.900 mean 10.491	1253		GPU 64 COO min 4.430 max 4.530 mean 4.461
1180		H min 11.109 max 11.109 mean 11.109	1254		CSR min 10.250 max 10.940 mean 10.603
1181	Row-Permute		1255		H min 10.934 max 10.945 mean 10.939
1182		GPU 64 COO min 4.170 max 4.630 mean 4.476	1256	Row-Column-Permute	
1183		CSR min 0.910 max 10.910 mean 10.257	1257		GPU 64 COO min 4.420 max 4.520 mean 4.450
1184		H min 11.098 max 11.104 mean 11.101	1258		CSR min 7.380 max 10.900 mean 10.598
1185	Row-Gradient		1259		H min 10.959 max 10.967 mean 10.963
1186		GPU 64 COO min 4.370 max 4.630 mean 4.529	1260	mult_dcop_01.mtx	
1187		CSR min 10.030 max 10.970 mean 10.624	1261	Regular	
1188		H min 11.109 max 11.109 mean 11.109	1262		GPU 64 COO min 3.420 max 3.630 mean 3.555
1189	Column-Gradient		1263		CSR min 3.650 max 4.090 mean 3.814
1190		GPU 64 COO min 4.250 max 4.640 mean 4.499	1264		H min 9.689 max 9.689 mean 9.689
1191		CSR min 8.510 max*11.010 mean 10.505	1265	Row-Permute	
1192		H min 11.328 max*11.333 mean 11.331	1266		GPU 64 COO min 3.450 max 3.580 mean 3.521
1193	Row-Column-Permute		1267		CSR min 3.610 max 4.150 mean 3.785
1194		GPU 64 COO min 4.350 max 4.640 mean 4.511	1268		H min 10.738 max 10.742 mean 10.740
1195		CSR min 10.040 max 10.790 mean 10.468	1269	Row-Gradient	
1196		H min 11.097 max 11.106 mean 11.101	1270		GPU 64 COO min 3.510 max* 3.660 mean 3.579
1197	lp_osa_07.mtx		1271		CSR min 3.650 max 4.160 mean 3.806
1198	Regular		1272		H min 10.576 max 10.585 mean 10.580
1199		GPU 64 COO min 0.460 max* 3.640 mean 3.456	1273	Column-Gradient	
1200		CSR min 5.570 max* 8.530 mean 8.106	1274		GPU 64 COO min 3.460 max 3.650 mean 3.584
1201		H min 8.412 max 8.412 mean 8.412	1275		CSR min 3.660 max* 4.240 mean 3.799
1202	Row-Permute		1276		H min 10.826 max*10.842 mean 10.836
1203		GPU 64 COO min 3.140 max 3.450 mean 3.367	1277	Row-Column-Permute	
1204		CSR min 7.600 max 8.070 mean 7.853	1278		GPU 64 COO min 3.470 max 3.580 mean 3.532
1205		H min 9.255 max 9.258 mean 9.256	1279		CSR min 3.680 max 3.980 mean 3.743
1206	Row-Gradient		1280		H min 10.738 max 10.742 mean 10.740
1207		GPU 64 COO min 3.190 max 3.610 mean 3.509	1281	mult_dcop_02.mtx	
1208		CSR min 0.000 max 8.260 mean 7.597	1282	Regular	
1209		H min 8.583 max 8.678 mean 8.670	1283		GPU 64 COO min 3.390 max 3.660 mean 3.585
1210	Column-Gradient		1284		CSR min 0.960 max 4.330 mean 4.162
1211		GPU 64 COO min 3.330 max 3.500 mean 3.416	1285		H min 9.689 max 9.689 mean 9.689
1212		CSR min 6.730 max 7.540 mean 7.199	1286	Row-Permute	
1213		H min 9.542 max* 9.604 mean 9.581	1287		GPU 64 COO min 3.310 max 3.600 mean 3.488
1214	Row-Column-Permute		1288		CSR min 0.620 max 4.290 mean 4.132
1215		GPU 64 COO min 3.290 max 3.430 mean 3.365	1289		H min 10.738 max 10.743 mean 10.740
1216		CSR min 7.390 max 8.060 mean 7.832	1290	Row-Gradient	
1217		H min 9.255 max 9.258 mean 9.256	1291		GPU 64 COO min 3.310 max* 3.670 mean 3.593
1218	Maragal_6.mtx		1292		CSR min 4.130 max* 4.430 mean 4.331
1219	Regular		1293		H min 10.576 max 10.584 mean 10.580
1220		GPU 64 COO min 4.160 max 4.310 mean 4.217	1294	Column-Gradient	
1221		CSR min 4.940 max 4.960 mean 4.956	1295		GPU 64 COO min 0.550 max 3.660 mean 3.486
1222		H min 9.930 max 9.930 mean 9.930	1296		CSR min 3.890 max 4.410 mean 4.275
1223	Row-Permute		1297		H min 10.831 max*10.843 mean 10.836
1224		GPU 64 COO min 4.220 max 4.240 mean 4.225	1298	Row-Column-Permute	
1225		CSR min 4.750 max*13.040 mean 5.133	1299		GPU 64 COO min 3.470 max 3.590 mean 3.542
1226		H min 10.776 max 10.778 mean 10.777	1300		CSR min 4.190 max 4.290 mean 4.242
1227	Row-Gradient		1301		H min 10.738 max 10.742 mean 10.740
1228		GPU 64 COO min 4.180 max* 4.450 mean 4.245	1302	mult_dcop_03.mtx	
1229		CSR min 4.880 max 4.940 mean 4.915	1303	Regular	
1230		H min 11.259 max*11.302 mean 11.281	1304		GPU 64 COO min 3.360 max* 3.660 mean 3.550
1231	Column-Gradient		1305		CSR min 3.650 max 4.090 mean 3.813
1232		GPU 64 COO min 4.200 max 4.250 mean 4.236	1306		H min 9.689 max 9.689 mean 9.689
1233		CSR min 4.800 max 4.890 mean 4.859	1307	Row-Permute	
1234		H min 12.022 max 12.073 mean 12.051	1308		GPU 64 COO min 3.450 max 3.580 mean 3.521
1235	Row-Column-Permute		1309		CSR min 3.610 max 4.160 mean 3.784
1236		GPU 64 COO min 4.210 max 4.230 mean 4.222	1310		H min 10.738 max 10.743 mean 10.740
1237		CSR min 4.860 max 4.890 mean 4.887	1311	Row-Gradient	
1238		H min 10.776 max 10.778 mean 10.778	1312		GPU 64 COO min 3.470 max 3.660 mean 3.572
1239	mhd4800a.mtx		1313		CSR min 3.640 max 4.190 mean 3.809
1240	Regular		1314		H min 10.572 max 10.584 mean 10.580
1241		GPU 64 COO min 4.570 max* 4.710 mean 4.608	1315	Column-Gradient	
1242		CSR min 12.690 max*13.940 mean 13.369	1316		GPU 64 COO min 3.430 max 3.650 mean 3.562
1243		H min 7.132 max 7.132 mean 7.132	1317		CSR min 3.670 max* 4.290 mean 3.793

1318		H	min 10.828 max*10.840 mean 10.834
1319	Row-Column-Permute		
1320		GPU 64 COO min	3.370 max 3.610 mean 3.502
1321		CSR min	3.610 max 3.970 mean 3.744
1322		H	min 10.738 max 10.741 mean 10.740
1323	OPF_3754.mtx		
1324	Regular		
1325		GPU 64 COO min	4.700 max* 4.930 mean 4.842
1326		CSR min	6.230 max* 6.600 mean 6.411
1327		H	min 8.393 max 8.393 mean 8.393
1328	Row-Premute		
1329		GPU 64 COO min	4.620 max 4.890 mean 4.787
1330		CSR min	5.780 max 6.310 mean 6.192
1331		H	min 11.265 max 11.272 mean 11.269
1332	Row-Gradient		
1333		GPU 64 COO min	4.570 max 4.870 mean 4.776
1334		CSR min	5.770 max 6.510 mean 6.302
1335		H	min 10.464 max 10.473 mean 10.468
1336	Column-Gradient		
1337		GPU 64 COO min	4.580 max 4.870 mean 4.756
1338		CSR min	5.630 max 6.180 mean 6.055
1339		H	min 11.394 max*11.401 mean 11.397
1340	Row-Column-Permute		
1341		GPU 64 COO min	4.610 max 4.900 mean 4.780
1342		CSR min	5.010 max 6.300 mean 6.113
1343		H	min 11.268 max 11.272 mean 11.270
1344	OPF_6000.mtx		
1345	Regular		
1346		GPU 64 COO min	3.780 max* 3.920 mean 3.864
1347		CSR min	4.270 max 4.360 mean 4.332
1348		H	min 8.799 max 8.799 mean 8.799
1349	Row-Premute		
1350		GPU 64 COO min	3.770 max 3.870 mean 3.821
1351		CSR min	3.970 max*11.050 mean 4.439
1352		H	min 11.872 max 11.877 mean 11.875
1353	Row-Gradient		
1354		GPU 64 COO min	3.700 max 3.870 mean 3.795
1355		CSR min	4.330 max 4.440 mean 4.403
1356		H	min 11.109 max 11.116 mean 11.113
1357	Column-Gradient		
1358		GPU 64 COO min	3.690 max 3.870 mean 3.804
1359		CSR min	4.260 max 4.340 mean 4.308
1360		H	min 12.041 max*12.045 mean 12.043
1361	Row-Column-Permute		
1362		GPU 64 COO min	3.780 max 3.860 mean 3.819
1363		CSR min	4.090 max 4.290 mean 4.259
1364		H	min 11.873 max 11.877 mean 11.876
1365	shermanACb.mtx		
1366	Regular		
1367		GPU 64 COO min	2.920 max* 3.140 mean 3.048
1368		CSR min	5.550 max 5.980 mean 5.803
1369		H	min 8.600 max 8.600 mean 8.600
1370	Row-Premute		
1371		GPU 64 COO min	2.760 max 3.020 mean 2.898
1372		CSR min	2.660 max 5.830 mean 5.632
1373		H	min 10.377 max 10.381 mean 10.379
1374	Row-Gradient		
1375		GPU 64 COO min	2.800 max 3.040 mean 2.944
1376		CSR min	5.330 max* 6.020 mean 5.742
1377		H	min 9.919 max 9.925 mean 9.922
1378	Column-Gradient		
1379		GPU 64 COO min	2.720 max 3.010 mean 2.926
1380		CSR min	0.000 max 5.840 mean 5.513
1381		H	min 10.587 max*10.596 mean 10.591
1382	Row-Column-Permute		
1383		GPU 64 COO min	2.780 max 3.030 mean 2.939
1384		CSR min	4.860 max 5.810 mean 5.667
1385		H	min 10.376 max 10.382 mean 10.379
1386	TSOPF_FS_b9_c6.mtx		
1387	Regular		
1388		GPU 64 COO min	0.000 max 0.000 mean 0.000
1389		CSR min	0.000 max 0.000 mean 0.000
1390		H	min 7.380 max 7.380 mean 7.380
1391	Row-Premute		

1392		GPU 64 COO min	4.540 max 4.940 mean 4.874
1393		CSR min	6.280 max 6.520 mean 6.403
1394		H	min 10.042 max 10.047 mean 10.044
1395	Row-Gradient		
1396		GPU 64 COO min	4.830 max 4.930 mean 4.875
1397		CSR min	5.790 max* 6.560 mean 6.289
1398		H	min 9.675 max 9.706 mean 9.692
1399	Column-Gradient		
1400		GPU 64 COO min	4.790 max* 4.960 mean 4.880
1401		CSR min	5.760 max 6.450 mean 6.204
1402		H	min 10.601 max*10.661 mean 10.626
1403	Row-Column-Permute		
1404		GPU 64 COO min	4.330 max 4.950 mean 4.845
1405		CSR min	5.740 max 6.500 mean 6.375
1406		H	min 10.041 max 10.046 mean 10.044
1407	TSOPF_RS_b39_c7.mtx		
1408	Regular		
1409		GPU 64 COO min	4.300 max* 4.430 mean 4.364
1410		CSR min	4.480 max 4.750 mean 4.716
1411		H	min 7.304 max 7.304 mean 7.304
1412	Row-Premute		
1413		GPU 64 COO min	4.260 max 4.400 mean 4.353
1414		CSR min	4.490 max 4.770 mean 4.734
1415		H	min 10.536 max 10.541 mean 10.539
1416	Row-Gradient		
1417		GPU 64 COO min	3.970 max 4.420 mean 4.338
1418		CSR min	4.620 max* 4.820 mean 4.789
1419		H	min 9.638 max 9.644 mean 9.641
1420	Column-Gradient		
1421		GPU 64 COO min	4.240 max 4.430 mean 4.368
1422		CSR min	4.710 max 4.770 mean 4.736
1423		H	min 11.129 max*11.222 mean 11.205
1424	Row-Column-Permute		
1425		GPU 64 COO min	4.260 max 4.410 mean 4.359
1426		CSR min	4.660 max 4.760 mean 4.738
1427		H	min 10.537 max 10.541 mean 10.539

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1428			
1429	mult_dcop_03.mtx		
1430	Regular		
1431		GPU 64 COO min	5.140 max* 5.140 mean 5.140
1432		CSR min	10.340 max*10.390 mean 10.365
1433		H	min 9.689 max 9.689 mean 9.689
1434	Row-Premute		
1435		GPU 64 COO min	4.970 max 4.990 mean 4.980
1436		CSR min	9.420 max 9.430 mean 9.425
1437		H	min 10.739 max 10.739 mean 10.739
1438	Row-Gradient		
1439		GPU 64 COO min	5.080 max 5.090 mean 5.085
1440		CSR min	9.720 max 10.300 mean 10.010
1441		H	min 10.579 max 10.582 mean 10.580
1442	Column-Gradient		
1443		GPU 64 COO min	5.030 max 5.120 mean 5.075
1444		CSR min	9.330 max 9.770 mean 9.550
1445		H	min 10.835 max*10.838 mean 10.836
1446	Row-Column-Permute		
1447		GPU 64 COO min	5.000 max 5.010 mean 5.005
1448		CSR min	7.580 max 9.460 mean 8.520
1449		H	min 10.739 max 10.741 mean 10.740
1450	mult_dcop_03.mtx		
1451	Regular		
1452		GPU 64 COO min	5.140 max* 5.140 mean 5.140
1453		CSR min	10.340 max*10.390 mean 10.365
1454		H	min 9.689 max 9.689 mean 9.689
1455	Row-Premute		
1456		GPU 64 COO min	4.970 max 4.990 mean 4.980
1457		CSR min	9.420 max 9.430 mean 9.425
1458		H	min 10.739 max 10.739 mean 10.739
1459	Row-Gradient		
1460		GPU 64 COO min	5.080 max 5.090 mean 5.085
1461		CSR min	9.720 max 10.300 mean 10.010
1462		H	min 10.579 max 10.582 mean 10.580

1463	Column-Gradient					1537			CSR min	6.360	max	7.450	mean	6.711
1464		GPU 64	COO	min	5.030	max	5.120	mean	5.075					
1465					CSR min	9.330	max	9.770	mean	9.550				
1466		H			min	10.835	max*10.838	mean	10.836					
1467	Row-Column-Permute													
1468		GPU 64	COO	min	5.000	max	5.010	mean	5.005					
1469					CSR min	7.580	max	9.460	mean	8.520				
1470		H			min	10.739	max	10.741	mean	10.740				
1471	mult_dcop_03.mtx													
1472	Regular													
1473		GPU 64	COO	min	5.130	max*	5.220	mean	5.142					
1474					CSR min	7.250	max*	9.320	mean	7.722				
1475		H			min	9.689	max	9.689	mean	9.689				
1476	Row-Premute													
1477		GPU 64	COO	min	4.980	max	5.030	mean	4.999					
1478					CSR min	6.460	max	8.470	mean	6.950				
1479		H			min	10.738	max	10.742	mean	10.740				
1480	Row-Gradient													
1481		GPU 64	COO	min	5.070	max	5.140	mean	5.088					
1482					CSR min	6.780	max	8.700	mean	7.268				
1483		H			min	10.572	max	10.584	mean	10.580				
1484	Column-Gradient													
1485		GPU 64	COO	min	4.980	max	5.030	mean	5.010					
1486					CSR min	6.390	max	7.640	mean	6.982				
1487		H			min	10.825	max*10.845	mean	10.836					
1488	Row-Column-Permute													
1489		GPU 64	COO	min	4.990	max	5.010	mean	4.997					
1490					CSR min	6.300	max	7.160	mean	6.636				
1491		H			min	10.738	max	10.743	mean	10.740				
1492	mult_dcop_01.mtx													
1493	Regular													
1494		GPU 64	COO	min	5.120	max*	5.140	mean	5.134					
1495					CSR min	6.990	max*	9.230	mean	7.546				
1496		H			min	9.689	max	9.689	mean	9.689				
1497	Row-Premute													
1498		GPU 64	COO	min	4.990	max	5.020	mean	5.004					
1499					CSR min	6.370	max	7.220	mean	6.771				
1500		H			min	10.738	max	10.743	mean	10.740				
1501	Row-Gradient													
1502		GPU 64	COO	min	5.060	max	5.100	mean	5.082					
1503					CSR min	6.730	max	7.720	mean	7.317				
1504		H			min	10.574	max	10.585	mean	10.580				
1505	Column-Gradient													
1506		GPU 64	COO	min	4.980	max	5.100	mean	5.012					
1507					CSR min	6.580	max	7.510	mean	7.054				
1508		H			min	10.828	max*10.842	mean	10.835					
1509	Row-Column-Permute													
1510		GPU 64	COO	min	4.970	max	5.000	mean	4.986					
1511					CSR min	6.390	max	7.050	mean	6.677				
1512		H			min	10.738	max	10.742	mean	10.740				
1513	mult_dcop_02.mtx													
1514	Regular													
1515		GPU 64	COO	min	5.120	max	5.140	mean	5.133					
1516					CSR min	6.950	max	7.590	mean	7.336				
1517		H			min	9.689	max	9.689	mean	9.689				
1518	Row-Premute													
1519		GPU 64	COO	min	4.970	max	4.990	mean	4.984					
1520					CSR min	6.440	max	7.110	mean	6.719				
1521		H			min	10.738	max	10.742	mean	10.740				
1522	Row-Gradient													
1523		GPU 64	COO	min	5.070	max*	5.150	mean	5.086					
1524					CSR min	6.650	max*	7.930	mean	7.304				
1525		H			min	10.574	max	10.587	mean	10.580				
1526	Column-Gradient													
1527		GPU 64	COO	min	4.980	max	5.040	mean	5.012					
1528					CSR min	6.520	max	7.650	mean	7.139				
1529		H			min	10.829	max*10.846	mean	10.836					
1530	Row-Column-Permute													
1531		GPU 64	COO	min	4.970	max	5.050	mean	4.983					
1532					CSR min	6.440	max	7.380	mean	6.779				
1533		H			min	10.738	max	10.743	mean	10.740				
1534	lp_fit2d.mtx													
1535	Regular													
1536		GPU 64	COO	min	3.960	max	3.960	mean	3.960					
1537														
1538														
1539	Row-Premute													
1540		GPU 64	COO	min	3.950	max*	3.980	mean	3.953					
1541					CSR min	6.330	max	7.400	mean	6.661				
1542		H			min	11.098	max	11.104	mean	11.101				
1543	Row-Gradient													
1544		GPU 64	COO	min	3.960	max	3.980	mean	3.961					
1545					CSR min	6.270	max*10.770	mean	7.017					
1546		H			min	11.109	max	11.109	mean	11.109				
1547	Column-Gradient													
1548		GPU 64	COO	min	3.940	max	3.960	mean	3.950					
1549					CSR min	6.270	max	7.370	mean	6.696				
1550		H			min	11.329	max*11.334	mean	11.331					
1551	Row-Column-Permute													
1552		GPU 64	COO	min	3.950	max	3.960	mean	3.952					
1553					CSR min	6.180	max	7.420	mean	6.641				
1554		H			min	11.098	max	11.105	mean	11.101				
1555	bloweya.mtx													
1556	Regular													
1557		GPU 64	COO	min	0.000	max	0.000	mean	0.000					
1558					CSR min	0.000	max	0.000	mean	0.000				
1559		H			min	7.205	max	7.205	mean	7.205				
1560	Row-Premute													
1561		GPU 64	COO	min	4.020	max	4.030	mean	4.023					
1562					CSR min	6.070	max	6.750	mean	6.340				
1563		H			min	11.025	max	11.031	mean	11.028				
1564	Row-Gradient													
1565		GPU 64	COO	min	4.090	max*	4.160	mean	4.111					
1566					CSR min	5.980	max*	7.370	mean	6.678				
1567		H			min	10.295	max	10.304	mean	10.300				
1568	Column-Gradient													
1569		GPU 64	COO	min	3.980	max	4.010	mean	3.995					
1570					CSR min	5.880	max	6.780	mean	6.295				
1571		H			min	10.881	max*10.887	mean	10.883					
1572	Row-Column-Permute													
1573		GPU 64	COO	min	4.020	max	4.030	mean	4.023					
1574					CSR min	5.970	max	6.420	mean	6.183				
1575		H			min	11.025	max	11.033	mean	11.028				
1576	lp_osa_07.mtx													
1577	Regular													
1578		GPU 64	COO	min	4.260	max*	4.270	mean	4.261					
1579					CSR min	6.440	max	7.640	mean	6.863				
1580		H			min	8.412	max	8.412	mean	8.412				
1581	Row-Premute													
1582		GPU 64	COO	min	4.200	max	4.200	mean	4.200					
1583					CSR min	6.020	max	7.030	mean	6.418				
1584		H			min	9.255	max	9.257	mean	9.256				
1585	Row-Gradient													
1586		GPU 64	COO	min	4.210	max	4.240	mean	4.226					
1587					CSR min	6.070	max*10.050	mean	6.498					
1588		H			min	8.607	max	8.678	mean	8.671				
1589	Column-Gradient													
1590		GPU 64	COO	min	4.170	max	4.190	mean	4.180					
1591					CSR min	5.610	max	7.300	mean	5.988				
1592		H			min	9.534	max*	9.601	mean	9.585				
1593	Row-Column-Permute													
1594		GPU 64	COO	min	4.190	max	4.190	mean	4.190					
1595					CSR min	6.070	max	7.000	mean	6.386				
1596		H			min	9.255	max	9.257	mean	9.256				
1597	ex19.mtx													

1611		GPU 64 COO min 5.760 max 5.840 mean 5.813	1685		H min 7.380 max 7.380 mean 7.380
1612		CSR min 9.710 max 14.220 mean 10.376	1686	Row-Premute	
1613		H min 11.873 max*11.882 mean 11.878	1687		GPU 64 COO min 4.130 max 4.170 mean 4.134
1614	Row-Column-Permute		1688		CSR min 6.180 max* 9.200 mean 6.796
1615		GPU 64 COO min 5.810 max 5.860 mean 5.838	1689		H min 10.041 max 10.046 mean 10.044
1616		CSR min 9.920 max 10.820 mean 10.240	1690	Row-Gradient	
1617		H min 11.836 max 11.841 mean 11.838	1691		GPU 64 COO min 4.150 max* 4.220 mean 4.163
1618	brainpc2.mtx		1692		CSR min 6.410 max 7.500 mean 6.816
1619	Regular		1693		H min 9.682 max 9.706 mean 9.693
1620		GPU 64 COO min 0.000 max 0.000 mean 0.000	1694	Column-Gradient	
1621		CSR min 0.000 max 0.000 mean 0.000	1695		GPU 64 COO min 4.080 max 4.110 mean 4.096
1622		H min 7.478 max 7.478 mean 7.478	1696		CSR min 6.020 max 7.220 mean 6.309
1623	Row-Premute		1697		H min 10.597 max*10.658 mean 10.631
1624		GPU 64 COO min 4.760 max 4.790 mean 4.773	1698	Row-Column-Permute	
1625		CSR min 6.930 max 7.780 mean 7.310	1699		GPU 64 COO min 4.120 max 4.140 mean 4.130
1626		H min 9.810 max 9.813 mean 9.811	1700		CSR min 6.210 max 7.200 mean 6.609
1627	Row-Gradient		1701		H min 10.041 max 10.046 mean 10.044
1628		GPU 64 COO min 4.820 max* 4.840 mean 4.831	1702	TSOPF_FS_b9_c6.mtx	
1629		CSR min 7.220 max 8.290 mean 7.583	1703	Regular	
1630		H min 9.721 max 9.725 mean 9.723	1704		GPU 64 COO min 0.000 max 0.000 mean 0.000
1631	Column-Gradient		1705		CSR min 0.000 max 0.000 mean 0.000
1632		GPU 64 COO min 4.760 max 4.820 mean 4.779	1706		H min 7.380 max 7.380 mean 7.380
1633		CSR min 6.870 max* 8.300 mean 7.393	1707	Row-Premute	
1634		H min 10.368 max*10.373 mean 10.370	1708		GPU 64 COO min 4.120 max 4.140 mean 4.129
1635	Row-Column-Permute		1709		CSR min 6.170 max 7.160 mean 6.664
1636		GPU 64 COO min 4.750 max 4.780 mean 4.765	1710		H min 10.041 max 10.045 mean 10.043
1637		CSR min 6.940 max 7.580 mean 7.298	1711	Row-Gradient	
1638		H min 9.809 max 9.814 mean 9.811	1712		GPU 64 COO min 4.150 max* 4.180 mean 4.162
1639	shermanACb.mtx		1713		CSR min 6.420 max 7.360 mean 6.723
1640	Regular		1714		H min 9.682 max 9.706 mean 9.693
1641		GPU 64 COO min 4.090 max* 4.130 mean 4.112	1715	Column-Gradient	
1642		CSR min 6.320 max* 7.200 mean 6.779	1716		GPU 64 COO min 4.080 max 4.120 mean 4.096
1643		H min 8.600 max 8.600 mean 8.600	1717		CSR min 5.880 max 7.090 mean 6.403
1644	Row-Premute		1718		H min 10.611 max*10.660 mean 10.637
1645		GPU 64 COO min 4.020 max 4.050 mean 4.036	1719	Row-Column-Permute	
1646		CSR min 5.670 max 6.460 mean 6.014	1720		GPU 64 COO min 4.130 max 4.140 mean 4.130
1647		H min 10.376 max 10.382 mean 10.379	1721		CSR min 6.330 max* 7.390 mean 6.695
1648	Row-Gradient		1722		H min 10.042 max 10.047 mean 10.044
1649		GPU 64 COO min 4.050 max 4.100 mean 4.074	1723	OPF_6000.mtx	
1650		CSR min 5.580 max 6.420 mean 5.996	1724	Regular	
1651		H min 9.918 max 9.924 mean 9.921	1725		GPU 64 COO min 7.270 max* 7.370 mean 7.293
1652	Column-Gradient		1726		CSR min 12.890 max*14.500 mean 13.566
1653		GPU 64 COO min 4.010 max 4.080 mean 4.033	1727		H min 8.799 max 8.799 mean 8.799
1654		CSR min 0.000 max 6.320 mean 5.527	1728	Row-Premute	
1655		H min 10.543 max*10.595 mean 10.589	1729		GPU 64 COO min 6.640 max 6.720 mean 6.678
1656	Row-Column-Permute		1730		CSR min 9.680 max 11.600 mean 10.040
1657		GPU 64 COO min 4.020 max 4.050 mean 4.036	1731		H min 11.873 max 11.877 mean 11.875
1658		CSR min 5.670 max 6.510 mean 6.092	1732	Row-Gradient	
1659		H min 10.377 max 10.381 mean 10.379	1733		GPU 64 COO min 7.090 max 7.140 mean 7.122
1660	cvxqp3.mtx		1734		CSR min 11.250 max 13.030 mean 12.142
1661	Regular		1735		H min 11.110 max 11.117 mean 11.114
1662		GPU 64 COO min 3.500 max* 3.540 mean 3.501	1736	Column-Gradient	
1663		CSR min 11.860 max*13.100 mean 12.694	1737		GPU 64 COO min 6.590 max 6.710 mean 6.644
1664		H min 8.646 max 8.646 mean 8.646	1738		CSR min 9.400 max 13.140 mean 9.991
1665	Row-Premute		1739		H min 12.040 max*12.046 mean 12.043
1666		GPU 64 COO min 3.360 max 3.370 mean 3.365	1740	Row-Column-Permute	
1667		CSR min 6.210 max 7.610 mean 6.631	1741		GPU 64 COO min 6.640 max 6.710 mean 6.679
1668		H min 11.027 max 11.032 mean 11.030	1742		CSR min 9.690 max 10.740 mean 10.050
1669	Row-Gradient		1743		H min 11.874 max 11.877 mean 11.875
1670		GPU 64 COO min 3.370 max 3.380 mean 3.376	1744	OPF_3754.mtx	
1671		CSR min 6.170 max 7.070 mean 6.499	1745	Regular	
1672		H min 11.059 max 11.068 mean 11.064	1746		GPU 64 COO min 4.430 max* 4.450 mean 4.443
1673	Column-Gradient		1747		CSR min 9.710 max*13.000 mean 11.377
1674		GPU 64 COO min 3.350 max 3.390 mean 3.371	1748		H min 8.393 max 8.393 mean 8.393
1675		CSR min 6.150 max 7.180 mean 6.531	1749	Row-Premute	
1676		H min 11.125 max*11.133 mean 11.130	1750		GPU 64 COO min 4.230 max 4.250 mean 4.240
1677	Row-Column-Permute		1751		CSR min 7.430 max 8.750 mean 7.986
1678		GPU 64 COO min 3.350 max 3.380 mean 3.364	1752		H min 11.266 max 11.272 mean 11.269
1679		CSR min 6.040 max 7.440 mean 6.603	1753	Row-Gradient	
1680		H min 11.028 max 11.033 mean 11.030	1754		GPU 64 COO min 4.370 max 4.420 mean 4.382
1681	case9.mtx		1755		CSR min 8.160 max 9.470 mean 8.682
1682	Regular		1756		H min 10.462 max 10.473 mean 10.468
1683		GPU 64 COO min 0.000 max 0.000 mean 0.000	1757	Column-Gradient	
1684		CSR min 0.000 max 0.000 mean 0.000	1758		GPU 64 COO min 4.210 max 4.240 mean 4.227

1759		CSR min 7.160 max 8.080 mean 7.595	1833	Row-Premute	
1760		H min 11.394 max*11.401 mean 11.398	1834		GPU 64 COO min 10.340 max 10.430 mean 10.362
1761	Row-Column-Permute		1835		CSR min 12.880 max 13.340 mean 13.057
1762		GPU 64 COO min 4.230 max 4.250 mean 4.243	1836		H min 10.777 max 10.778 mean 10.777
1763		CSR min 7.230 max 8.940 mean 8.056	1837	Row-Gradient	
1764		H min 11.264 max 11.271 mean 11.269	1838		GPU 64 COO min 10.650 max*10.740 mean 10.688
1765	c-47.mtx		1839		CSR min 12.310 max 13.670 mean 12.562
1766	Regular		1840		H min 11.247 max 11.300 mean 11.281
1767		GPU 64 COO min 5.320 max* 5.340 mean 5.329	1841	Column-Gradient	
1768		CSR min 8.890 max* 9.590 mean 9.249	1842		GPU 64 COO min 10.340 max 10.440 mean 10.398
1769		H min 8.364 max 8.364 mean 8.364	1843		CSR min 9.480 max 10.110 mean 9.782
1770	Row-Premute		1844		H min 12.023 max*12.069 mean 12.047
1771		GPU 64 COO min 5.240 max 5.250 mean 5.241	1845	Row-Column-Permute	
1772		CSR min 7.790 max 8.890 mean 8.214	1846		GPU 64 COO min 10.330 max 10.380 mean 10.356
1773		H min 10.059 max 10.063 mean 10.061	1847		CSR min 12.840 max 13.530 mean 13.119
1774	Row-Gradient		1848		H min 10.776 max 10.778 mean 10.777
1775		GPU 64 COO min 5.230 max 5.260 mean 5.242	1849	aft01.mtx	
1776		CSR min 7.080 max 8.050 mean 7.673	1850	Regular	
1777		H min 10.206 max 10.226 mean 10.218	1851		GPU 64 COO min 3.680 max* 3.690 mean 3.688
1778	Column-Gradient		1852		CSR min 13.860 max*14.830 mean 14.560
1779		GPU 64 COO min 5.080 max 5.120 mean 5.105	1853		H min 7.811 max 7.811 mean 7.811
1780		CSR min 5.780 max 6.970 mean 6.359	1854	Row-Premute	
1781		H min 11.205 max*11.233 mean 11.222	1855		GPU 64 COO min 3.510 max 3.530 mean 3.513
1782	Row-Column-Permute		1856		CSR min 6.420 max 10.520 mean 7.265
1783		GPU 64 COO min 5.220 max 5.250 mean 5.227	1857	Row-Gradient	
1784		CSR min 7.860 max 8.710 mean 8.247	1858		H min 11.161 max*11.170 mean 11.165
1785		H min 10.059 max 10.064 mean 10.061	1859		GPU 64 COO min 3.630 max 3.670 mean 3.643
1786	mhd4800a.mtx		1860		CSR min 10.760 max 13.510 mean 12.199
1787	Regular		1861		H min 10.248 max 10.265 mean 10.258
1788		GPU 64 COO min 3.090 max* 3.100 mean 3.098	1862	Column-Gradient	
1789		CSR min 11.570 max*12.290 mean 12.092	1863		GPU 64 COO min 3.510 max 3.520 mean 3.519
1790		H min 7.132 max 7.132 mean 7.132	1864		CSR min 6.490 max 11.230 mean 7.645
1791	Row-Premute		1865		H min 11.112 max 11.121 mean 11.117
1792		GPU 64 COO min 3.020 max 3.020 mean 3.020	1866	Row-Column-Permute	
1793		CSR min 5.560 max 7.270 mean 6.007	1867		GPU 64 COO min 3.510 max 3.540 mean 3.515
1794		H min 10.959 max*10.968 mean 10.963	1868		CSR min 6.510 max 11.650 mean 7.311
1795	Row-Gradient		1869		H min 11.161 max 11.168 mean 11.165
1796		GPU 64 COO min 3.080 max 3.100 mean 3.088	1870	TSOPF_RS_b39_c7.mtx	
1797		CSR min 10.250 max 12.150 mean 11.340	1871	Regular	
1798		H min 9.509 max 9.528 mean 9.520	1872		GPU 64 COO min 5.970 max* 6.010 mean 5.988
1799	Column-Gradient		1873		CSR min 12.470 max*21.120 mean 13.816
1800		GPU 64 COO min 3.020 max 3.050 mean 3.026	1874		H min 7.304 max 7.304 mean 7.304
1801		CSR min 5.530 max 10.580 mean 6.432	1875	Row-Premute	
1802		H min 10.933 max 10.946 mean 10.939	1876		GPU 64 COO min 5.840 max 5.870 mean 5.856
1803	Row-Column-Permute		1877		CSR min 10.780 max 15.810 mean 11.425
1804		GPU 64 COO min 3.020 max 3.020 mean 3.020	1878		H min 10.537 max 10.540 mean 10.539
1805		CSR min 5.510 max 6.830 mean 6.136	1879	Row-Gradient	
1806		H min 10.959 max 10.967 mean 10.963	1880		GPU 64 COO min 5.950 max 6.000 mean 5.975
1807	gen4.mtx		1881		CSR min 11.520 max 17.250 mean 12.799
1808	Regular		1882		H min 9.638 max 9.646 mean 9.641
1809		GPU 64 COO min 3.300 max* 3.320 mean 3.308	1883	Column-Gradient	
1810		CSR min 5.250 max 6.340 mean 5.705	1884		GPU 64 COO min 5.790 max 5.860 mean 5.827
1811		H min 9.234 max 9.234 mean 9.234	1885		CSR min 10.500 max 14.080 mean 11.237
1812	Row-Premute		1886		H min 11.128 max*11.223 mean 11.209
1813		GPU 64 COO min 3.290 max 3.310 mean 3.299	1887	Row-Column-Permute	
1814		CSR min 5.190 max 7.420 mean 5.683	1888		GPU 64 COO min 5.850 max 5.870 mean 5.855
1815		H min 10.249 max 10.254 mean 10.252	1889		CSR min 10.790 max 15.250 mean 11.718
1816	Row-Gradient		1890		H min 10.537 max 10.541 mean 10.539
1817		GPU 64 COO min 3.300 max 3.310 mean 3.301	1891	mult_dcop_03.mtx	
1818		CSR min 5.370 max 6.310 mean 5.659	1892	Regular	
1819		H min 9.934 max 9.958 mean 9.948	1893		GPU 64 COO min 5.130 max* 5.220 mean 5.142
1820	Column-Gradient		1894		CSR min 7.250 max* 9.320 mean 7.722
1821		GPU 64 COO min 3.240 max 3.260 mean 3.249	1895		H min 9.689 max 9.689 mean 9.689
1822		CSR min 5.090 max* 8.660 mean 5.546	1896	Row-Premute	
1823		H min 10.853 max*10.873 mean 10.864	1897		GPU 64 COO min 4.980 max 5.030 mean 4.999
1824	Row-Column-Permute		1898		CSR min 6.460 max 8.470 mean 6.950
1825		GPU 64 COO min 3.290 max 3.320 mean 3.296	1899		H min 10.738 max 10.742 mean 10.740
1826		CSR min 5.190 max 7.550 mean 5.659	1900	Row-Gradient	
1827		H min 10.249 max 10.255 mean 10.252	1901		GPU 64 COO min 5.070 max 5.140 mean 5.088
1828	Maragal_6.mtx		1902		CSR min 6.780 max 8.700 mean 7.268
1829	Regular		1903		H min 10.572 max 10.584 mean 10.580
1830		GPU 64 COO min 10.580 max 10.620 mean 10.599	1904	Column-Gradient	
1831		CSR min 15.620 max*16.470 mean 15.832	1905		GPU 64 COO min 4.980 max 5.030 mean 5.010
1832		H min 9.930 max 9.930 mean 9.930	1906		CSR min 6.390 max 7.640 mean 6.982

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1907           H           min 10.825 max 10.845 mean 10.836
1908 Row-Column-Permute
1909           GPU 64 COO min 4.990 max 5.010 mean 4.997
1910           CSR min 6.300 max 7.160 mean 6.636
1911           H           min 10.738 max 10.743 mean 10.740

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