CSCE 435 Group project

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2. Project topic

Parallelized Sorting Algorithms

2a. Project topic

Sorting algorithms We will compare each of the four algorithms (Bucket Sort, QuickSort, Sample Sort, Bubble Sort) by implementing in MPI as well as Cuda. We plan to use reverse sorted, random, and 10% noisy data and compare each of the implementations across those as well.

2b. Pseudocode for each parallel algorithm

Bucket Sort

```
function bucketsort(data,n_buckets)
        create n_buckets empty arrays
        loop over data:
                add data[i] to correct bucket

        for each bucket:
                bitonicsort(bucket)


        for each bucket:
                copy bucket contents to answer array
```

QuickSort

create function that takes in an array, two integers, low and high

```
        function
                set integer as pivot, equal to element at position high in array
                set integer as k, equal to low - 1
                for each element from low to high
                        if element at array is less than pivot
                                k increases
                                swap the numbers at position element and k

                end for
                swap element at k+1 and element at high
                return k+1
```

create second function takes in array , two integers, low and high

```
        in function
                if low is less than high
                        set integer as p, call first function with values given
                        recursive call with array, low and p-1
                        recursive call with array, p+1, and high
                end if
```

in main function call second function with array, 0 and n-1, n being the size of the array.

Bubble Sort

create function that takes in an array of items

```
function bubbleSort(list: array of items)
        loop = list.count
        for i = 0 to loop-1
                boolean swapped = false
                for j = 0 to loop-1
                        if list at index j > list at index j+1
                                swap(list at index j, list at index j+1)
                                swapped = true
                        if (not swapped)
                                break
        return list
```

Sample Sort

With unsorted array of size n Create m buckets (m likely # of threads)

```
for element in array
    bucket index = element index / m
    add element to bucket[ bucket index]

for each bucket in buckets
    sort bucket with quicksort

need m-1 pivot elements

piv_num = m-1
```

create sample_selection array

```
for each bucket in buckets
    mod_number = ceil(number of elements in bucket /(piv_num+1))
    for i in range of 1 and piv_num
        append bucket[imod_number] element to sample_selection


Global splitters = []

sort sample_selection

mod_number= ceil (number of elements in sample_selection/ (piv_num +1))
for i in range of 1 and piv_num
    append sample_selection[ i mod_number] to global splitters
```

we should have m-1 global splitters, now use these splitters for bucket sort perform bucket sort given m buckets and the bucket partitions being the global splitters

2c. Evaluation Plan - what and how will you measure and compare

For MPI: Processes: 2, 4, 8, 16, 32, 64, 128, 256, 512, 1024 Input Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$, 2^28

For CUDA: Threads: 64, 128, 256, 512, 1024 Input Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$, 2^28

We will be measuring strong scaling, weak scaling, and speedups of our algorithms and also compare how each of the datatypes (random, sorted, reverse sorted, and 1% perturbed) compare against each other.

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3. Project implementation

Pseudocode of our algorithms. We used Caliper Marks to time each section of our code and analyzed the resulting Caliper files. All implementations have at least the following marks: main, data_init, comp, comm, and correctness_check

Bucket Sort

Required Code Regions: data_init, comm, comp, comm_large, comp_large, comm_small comp_small, correctness_check

CUDA Implementation (Pseudocode):

```
function bucketsort(data,sizes,n_buckets)
        compute thread index
        add data of index to correct bucket
    increment bucket size

function main()
    generateData(data) //on host

    copy data to device
    bucketSort(data,sizes,n_buckets) //on kernel
    for each bucket:
            bitonicsort(bucket) //on kernel
    for each bucket:
            copy bucket contents to answer array on host
```

MPI Implementation (Pseudocode):

```
function main()
    generateData(data)

    loop over local data
        add data to correct bucket
        increment bucket size

    add then broadcast bucket sizes

    sort local bucket

    gather all buckets together
```

Quicksort

CUDA Implementation (Pseudocode):

```
int THREADS;
int BLOCKS;
int NUM_VALS;

const char* bitonic_sort_step_region = "bitonic_sort_step";
const char* cudaMemcpy_host_to_device = "cudaMemcpy_host_to_device";
const char* cudaMemcpy_device_to_host = "cudaMemcpy_device_to_host";

function float random_float() {
  return (float)rand() / (float)RAND_MAX;
}

function void array_fill(float* arr, int length) {
  srand(time(NULL));
  for i = 0 to length - 1 do
    arr[i] = random_float();
  end for
}

function void quick_sort_step(float* dev_values, int l, int h) {
  Launch a CUDA kernel to perform a step of the quicksort on dev_values within the range [l, h].
  // This part contains GPU-specific CUDA code.
}

function void quick_sort(float* values, int low, int high) {
  Allocate GPU memory for dev_values.
  Copy values from the CPU to the GPU (dev_values).
  Perform the quicksort step on dev_values using CUDA.
  Copy the sorted values back from the GPU to the CPU (values).
  Free the GPU memory.
}

function int main(int argc, char* argv[]) {
  Parse command line arguments to set THREADS and NUM_VALS.
  Calculate BLOCKS based on NUM_VALS and THREADS.

  Initialize the Caliper configuration manager.

  Allocate memory for an array of float values.

  Record the start time.

  Perform the quicksort on the array of values.

  Record the stop time.

  Flush the Caliper configuration manager to capture profiling information.
}
```

Bubble Sort

Required Code Regions: data_init, comm, comp, comm_large, comp_large, comm_small comp_small, correctness_check

Cuda Implementation (Psuedocode):

```
// Function to generate a random float
function random_float() -> float
    return random float value between 0 and 1

// Function to fill an array with random float values
function array_fill(arr: float[], length: int)
    for i from 0 to length - 1
        arr[i] = random_float()

// Function to verify the correctness of the sorted array
function verify(values: float[]) -> int
    for i from 0 to length of values - 2
        if values[i] > values[i+1]
            return -1
    return 1

// CUDA kernel for a single step of bubble sort
function bubble_sort_step(dev_values: float[])
    i = threadIdx.x + blockDim.x * blockIdx.x
    next = i + 1
    if next < d_NUM_VALS
        if dev_values[i] > dev_values[next]
            swap dev_values[i] and dev_values[next]

// Function to perform bubble sort on the GPU
function bubble_sort(values: float[])
    allocate device memory for dev_values
    copy values from host to dev_values
    set d_NUM_VALS to NUM_VALS
    define grid and block dimensions
    for i from 0 to NUM_VALS - 2
        call bubble_sort_step kernel with dev_values as argument
    synchronize GPU
    copy dev_values from device to host
    free device memory

// Main function
function main(argc: int, argv: string[]) -> int
    THREADS = convert argv[1] to int
    NUM_VALS = convert argv[2] to int
    BLOCKS = NUM_VALS / THREADS
    start = current time
    allocate memory for values
    call array_fill with values and NUM_VALS as arguments
    call bubble_sort with values as argument
    stop = current time
    size = NUM_VALS * size of float
    data_size_gb = kernel_call * size * 4 * (1e-9) // Size in GB
```

```
kernel_execution_time_s = (stop - start) / CLOCKS_PER_SEC // Kernel execution time in seconds
effective_bandwidth_gb_s = data_size_gb / kernel_execution_time_s
if verify(values)
    print "Sort successful"
else
    print "Sort unsuccessful"
free memory for values
return 0
```

MPI Implementation (Pseudocode):

```
function partnerFind(int phase, int rank)
    if phase % 2 == 0
        if rank % 2 == 0
            partner = rank + 1
        else
            partner = rank - 1
        end if
    else
        if rank % 2 == 0
            partner = rank - 1
        else
            partner = rank + 1
        end if
    end if
    return partner
end function

function verify(data: array of double, dataSize: int) -> int
    for i from 0 to dataSize - 2
        if data[i] > data[i+1]
            return -1
        end if
    end for
    return 1
end function

function main(argc: int, argv: array of string) -> int
    my_rank = get_MPI_Comm_rank(MPI_COMM_WORLD)
    numprocs = get_MPI_Comm_size(MPI_COMM_WORLD)

    IF numprocs < 2 THEN
        MPI_Abort(MPI_COMM_WORLD, -1)
    END IF

    mode = 0
    dataSize = 100

    dataSize = convert_to_integer(argv[1])
    mode = convert_to_integer(argv[2])

    local_data = dataSize / numprocs
    test = new array of size local_data
    final_arr = null

    genData(dataSize, mode, test)

    Initialize arrays temp and data
```

```
    FOR i = 0 TO numprocs
        partner = partnerFind(i, my_rank)

        IF partner >= numprocs OR partner < 0 THEN
            CONTINUE
        END IF

        IF my_rank % 2 == 0 THEN
            MPI_Send(test, local_data, MPI_DOUBLE, partner, 0, MPI_COMM_WORLD)
            MPI_Recv(temp, local_data, MPI_DOUBLE, partner, 0, MPI_COMM_WORLD, MPI_STATUS_IGNORE)
        ELSE
            MPI_Recv(temp, local_data, MPI_DOUBLE, partner, 0, MPI_COMM_WORLD, MPI_STATUS_IGNORE)
            MPI_Send(test, local_data, MPI_DOUBLE, partner, 0, MPI_COMM_WORLD)
        END IF

        Merge test and temp arrays into data array
        Sort data array

        half_data = data + local_data

        IF my_rank < partner THEN
            Copy data to test
        ELSE
            Copy half_data to test
        END IF
    END FOR

    IF my_rank == MASTER THEN
        final_arr = new array of size dataSize
    END IF

    MPI_Gather(test, local_data, MPI_DOUBLE, final_arr, local_data, MPI_DOUBLE, 0, MPI_COMM_WORLD)

    IF my_rank == MASTER THEN
        IF verify(final_arr, dataSize) == 1 THEN
            PRINT "Sort successful"
        ELSE
            PRINT "Sort unsuccessful"
        END IF
    END IF

    return 0
end function
```

Sample Sort

Required Code Regions: data_init, comm, comp, comm_large, comp_large, comm_small comp_small, correctness_check

MPI Implementation:

For sample sort, the first MPI gather gathers all the splitters from the processors and combines them. Then, MPI all to all will send data from all processes to the communicators, the buckets are sorted locally, and then eventually are gathered together to form a sorted array

CUDA Implementation:

In the cuda kernel, the computation for sorting each block/bucket is performed. After each bucket is sorted, we obtain the splitters from them with a cuda memcpy, and then each kernel places elements into their respective buckets. Another memcpy is used to copy the sorted values from the GPU to the main process into one array.

3b. Collect Metadata

We collect the following metadata in our implementations: Launch date of the job, libraries used, command line used to launch the job, name of the cluster, name of the algorithm, what the programming model is (MPI or CUDA), the datatype of input elements, size of the datatype, number of elements in the input dataset, what the input type is, number of processesors for MPI, number of threads for CUDA, number of blocks for CUDA, our group number, and where we got our source code from.

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4. Performance evaluation

In our performance evaluation, we analyzed the time taken to finish sorting an array of varying sizes using parallelization methods for bucket sort, quicksort, bubble sort, and sample sort. We looked at the time for main, data initialization, communication, computation, and correctness check. We also varied the number of processors (for MPI) and threads (for CUDA) to further analyze how the number of processors and threads would affect the performance of each algorithm. Lastly, we had a total of 4 input types tested, those being randomly generated data, sorted data, reverse sorted data, and 1% perturbed data to see how the performance of each algorithm would be affected from it.

4a. Varying Parameters

For our parameters, each implementation had varying degrees of success with running them. In the end, we decided to use 2^20 input size to compare our algorithms to each other. Here are our parameters for each algorithm:

Bucket Sort:

MPI:

Number of Processes: 2, 4, 8, 16, 32, 64, 128, 256, 512

Data Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$, 2^28

CUDA:

Number of Threads: 64, 128, 256, 512, 1024

Data Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$, 2^28

Quicksort:

MPI:

Number of Processes: 2, 4, 8, 16, 32, 64, 128, 256, 512, 1024

Data Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$, 2^28

CUDA:

Number of Threads: 64, 128, 256, 512, 1024

Data Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$, 2^28

Bubble Sort:

MPI:

Number of Processes: 2, 4, 8, 16, 32, 64, 128, 256, 512, 1024

Data Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$

CUDA:

Number of Threads: 64, 128, 256, 512, 1024

Data Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$

Sample Sort:

MPI:

Number of Processes: 2, 4, 8, 16, 32, 64

Data Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$, 2^28

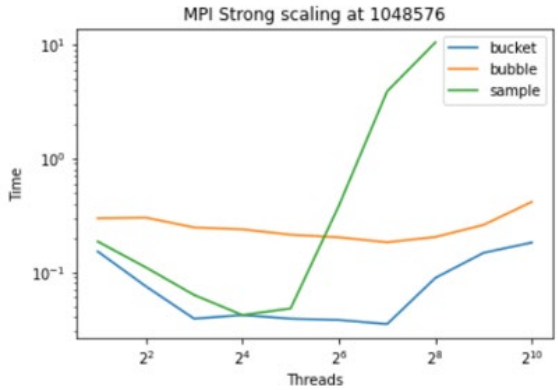
CUDA:

Number of Threads: 64, 128, 256, 512, 1024

Data Size: $2^{16, 2}18$, $2^{20, 2}22$, $2^{24, 2}26$, 2^28

4b Performance Analysis of Sorting Algorithms

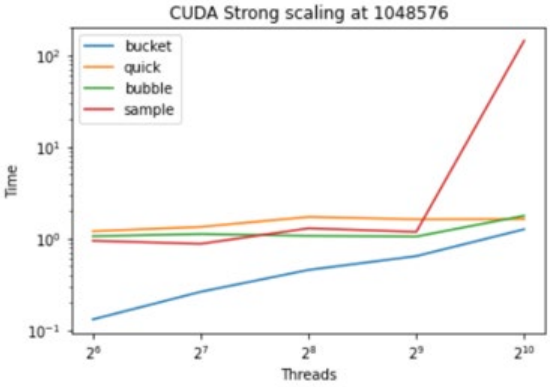
MPI Comparison between Algorithms:



For MPI, bucket sort is clearly the best implementation, even though communication time starts to become a limiting factor as the number of threads increases. This plot was done at 1048576 because that was the size that worked best across implementations.

Sample sort was very inefficient and bubble sort was near constant.

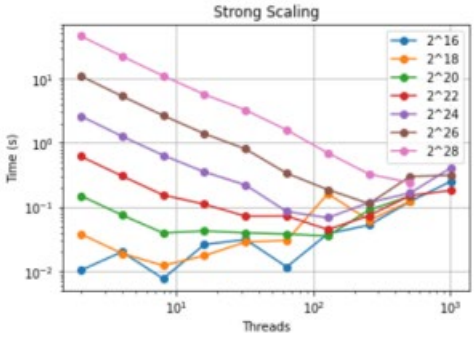
CUDA Comparison between Algorithms:

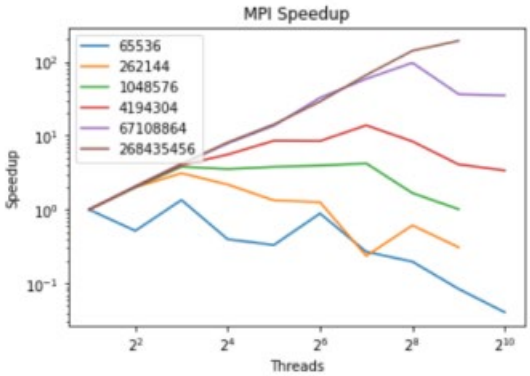


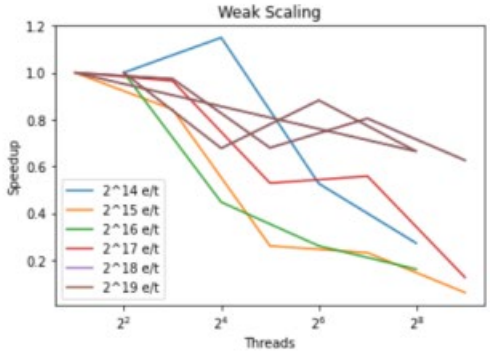
For CUDA, bucket sort is still the best implementation by absolute terms. However, the odd-even version of bubble sort is more stable to thread sizes and would likely perform better across a variety of problems. This plot was also done at 1048576 because that was the size that worked best across implementations.

Bucket Sort:

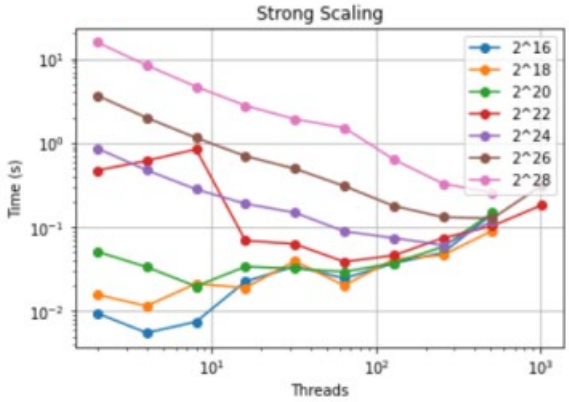
MPI Comparisons:

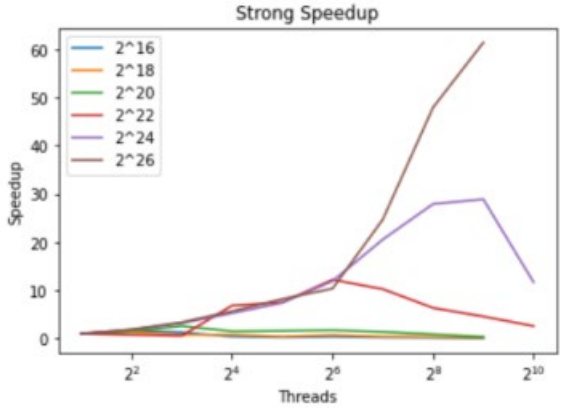


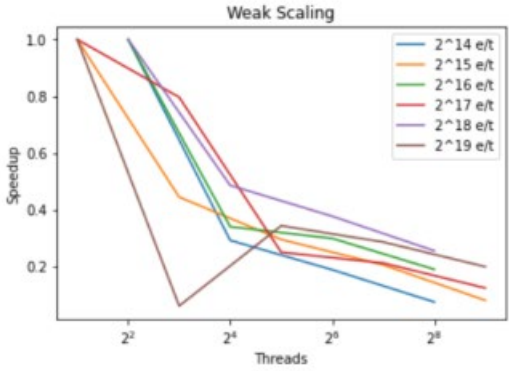




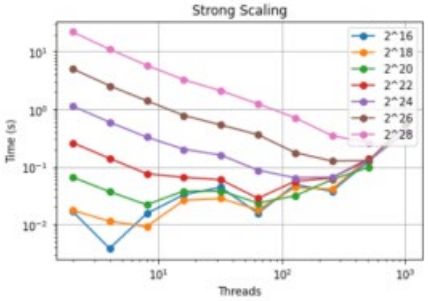
MPI scales very well with bucket sort. As thread count increases, the communication time increases because not only the data but also the bucket sizes and offsets must be communicated between processes, and this is a lot of overhead multiple times. We do see speedup of up to 100x for the largest input sizes which is good performance. The speedup is not quite enough to support weak scaling across the main of the program, but weak scaling is better for larger input sizes.

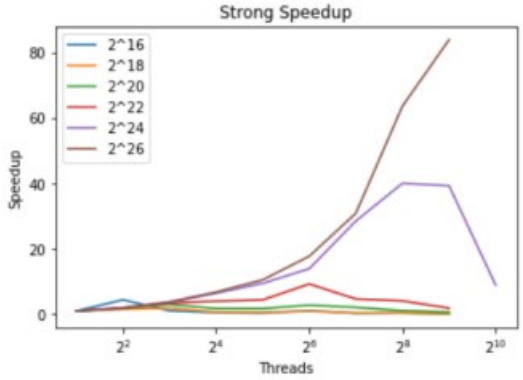


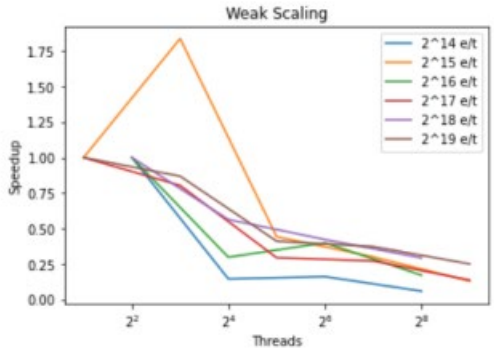




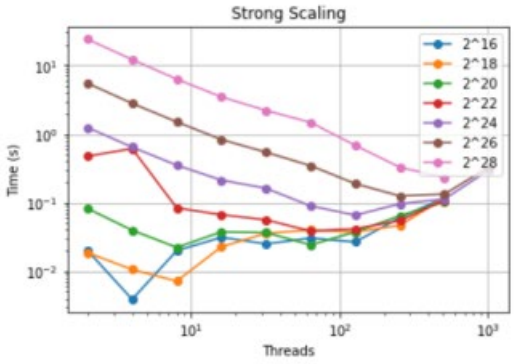
With sorted data, the algorithm works better than random with smaller input sizes, likely because it distributes more uniformly into buckets and is not subject to random fluctuation. This makes the speedup worse, especially for the small input sizes as it is faster at the baseline.

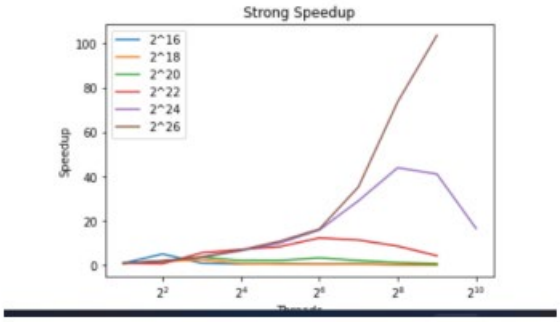


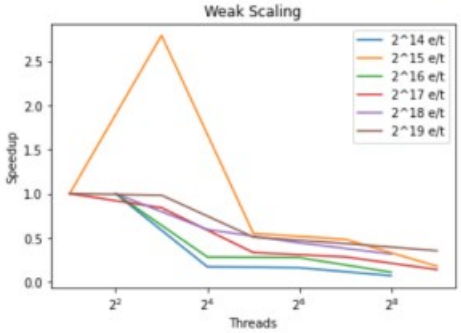




Reverse sorting follows a very similar trend to sorted data. Since everything is sorted into buckets and then combined, this type of symmetry is to be somewhat expected.

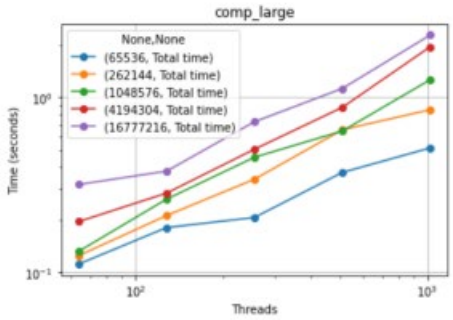


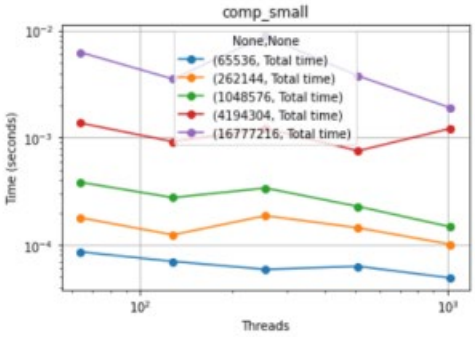


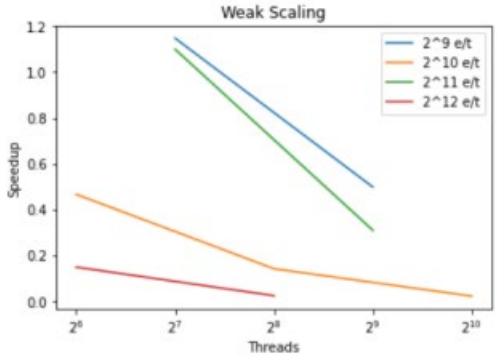


Adding 1% randomness does not change the overall performance that much from the fully sorted implementation. The bucket sizes are still very close to evenly distributed.

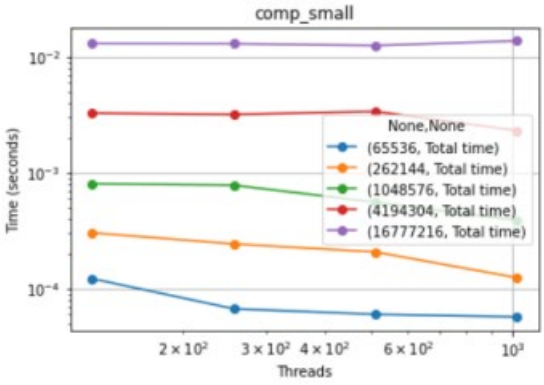
CUDA Comparisons:

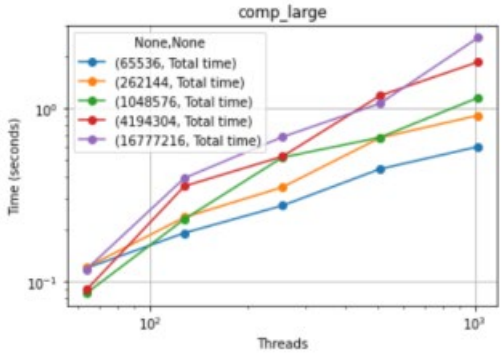


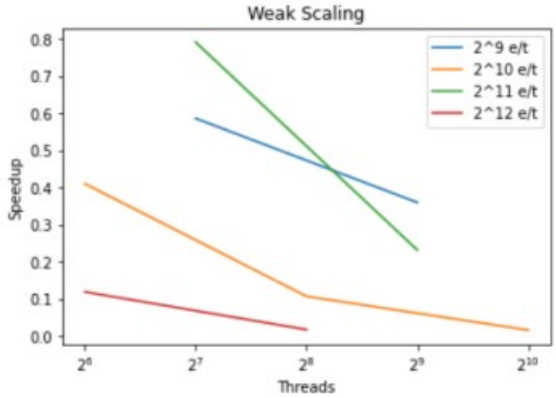




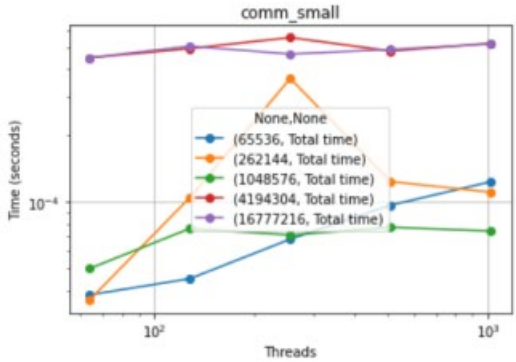
CUDA exhibits exceptionally poor performance. This is random input. The comp_small region represents sorting the data into buckets, where the number of buckets is equal to the number of threads. This has a moderate parallelization, and is hindered by the necessity of using atomics to increment the counts of the numbers in each bucket. The comp_large region represents the region of sorting all the buckets. I tried bitonic as well as thrust::sort, and both of them had qualitiatively similar results. The challenge is that although the sorting of one bucket is parallellized, each bucket must be sorted. So more threads means more buckets means more sorting, which is why comp_large increases with threads.

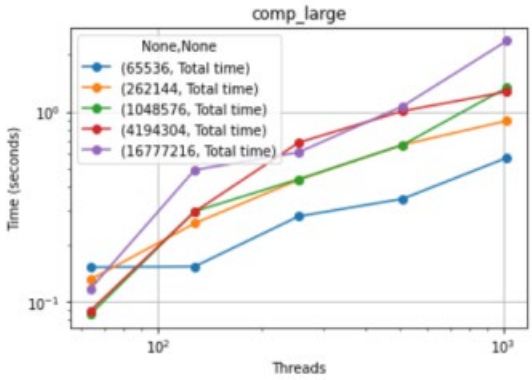

comp_small
Time (seconds)
Threads
None,None
(65536, Total time)
(262144, Total time)
(1048576, Total time)
(4194304, Total time)
(16777216, Total time)

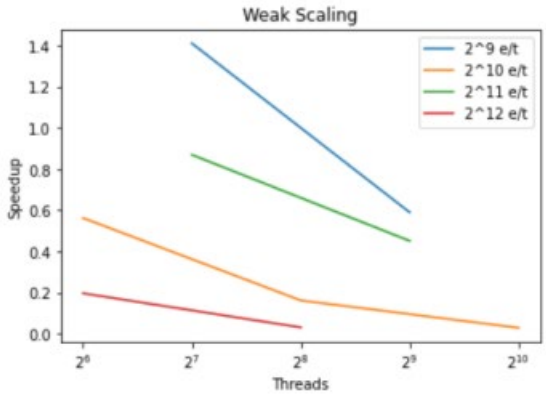

comp_large
Time (seconds)
Threads
None,None
(65536, Total time)
(262144, Total time)
(1048576, Total time)
(4194304, Total time)
(16777216, Total time)


Weak Scaling
Speedup
Threads
2^9 e/t
2^10 e/t
2^11 e/t
2^12 e/t

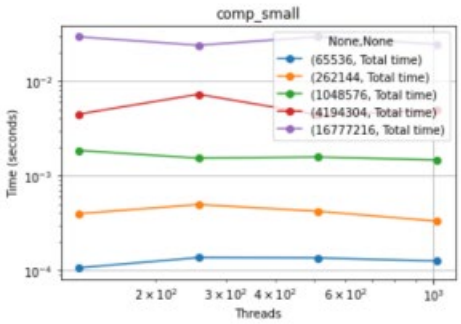
With sorted input, we see less parallelization in the sorting data into buckets region. This is because the data is sorted so each thread in a block will be adding to the same bucket, resulting in longer waiting times for the atomic incrementing of the counts of the numbers in each bucket.

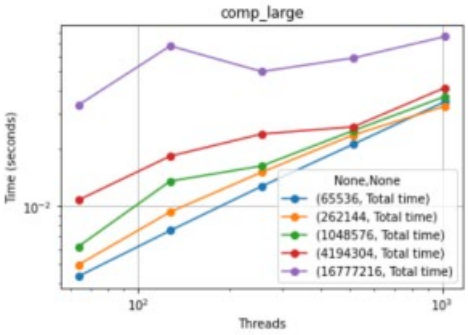


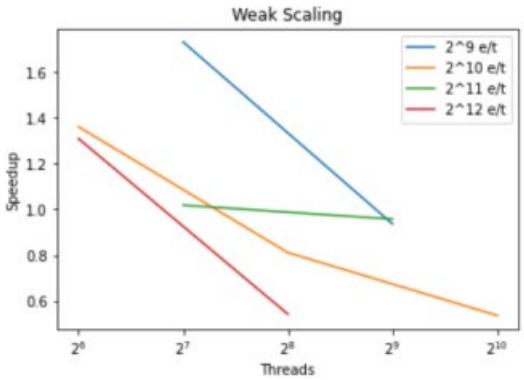




Reverse sorted input shows a similar trend to sorted input, again as bucket sort is fairly symmetric.





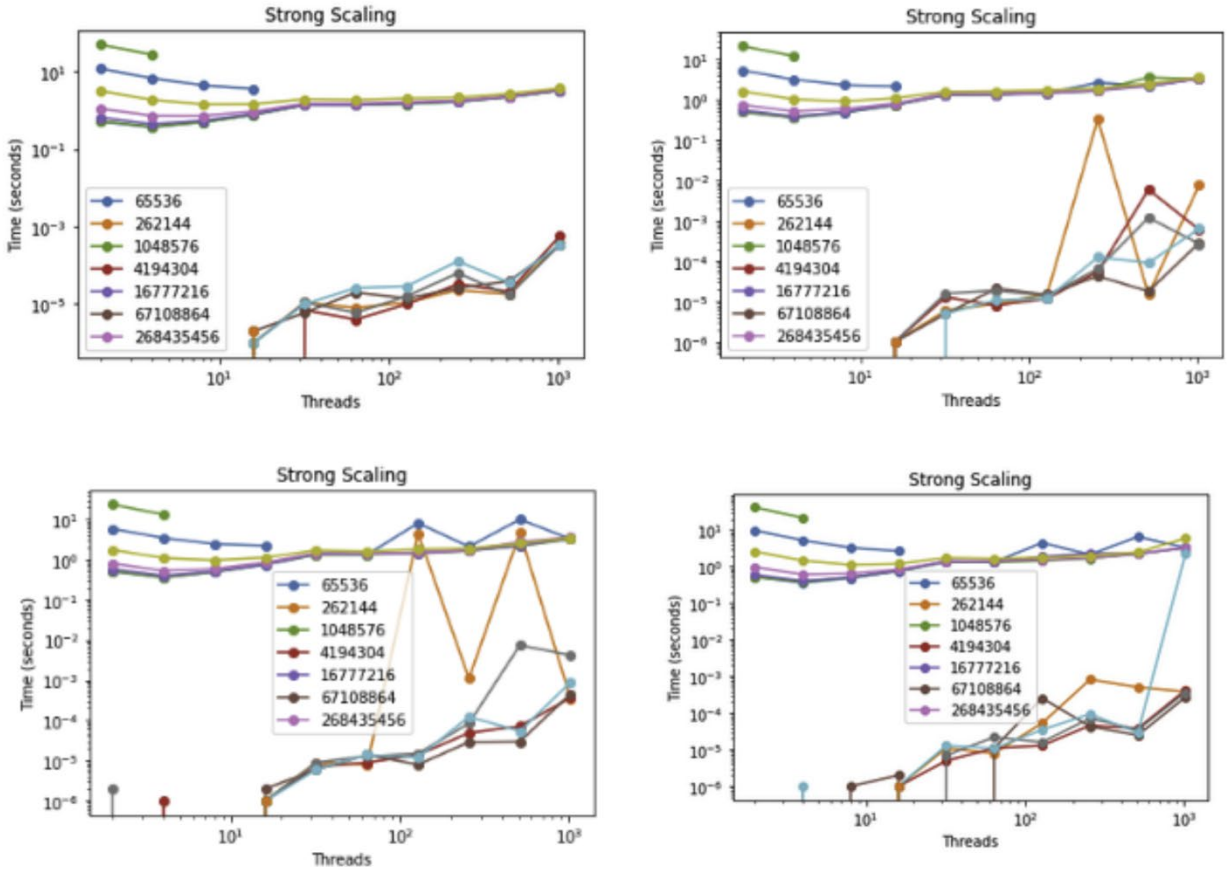


Perturbing the data by 1% does not significantly change performance, but does make it fluctuate a little.

QuickSort:

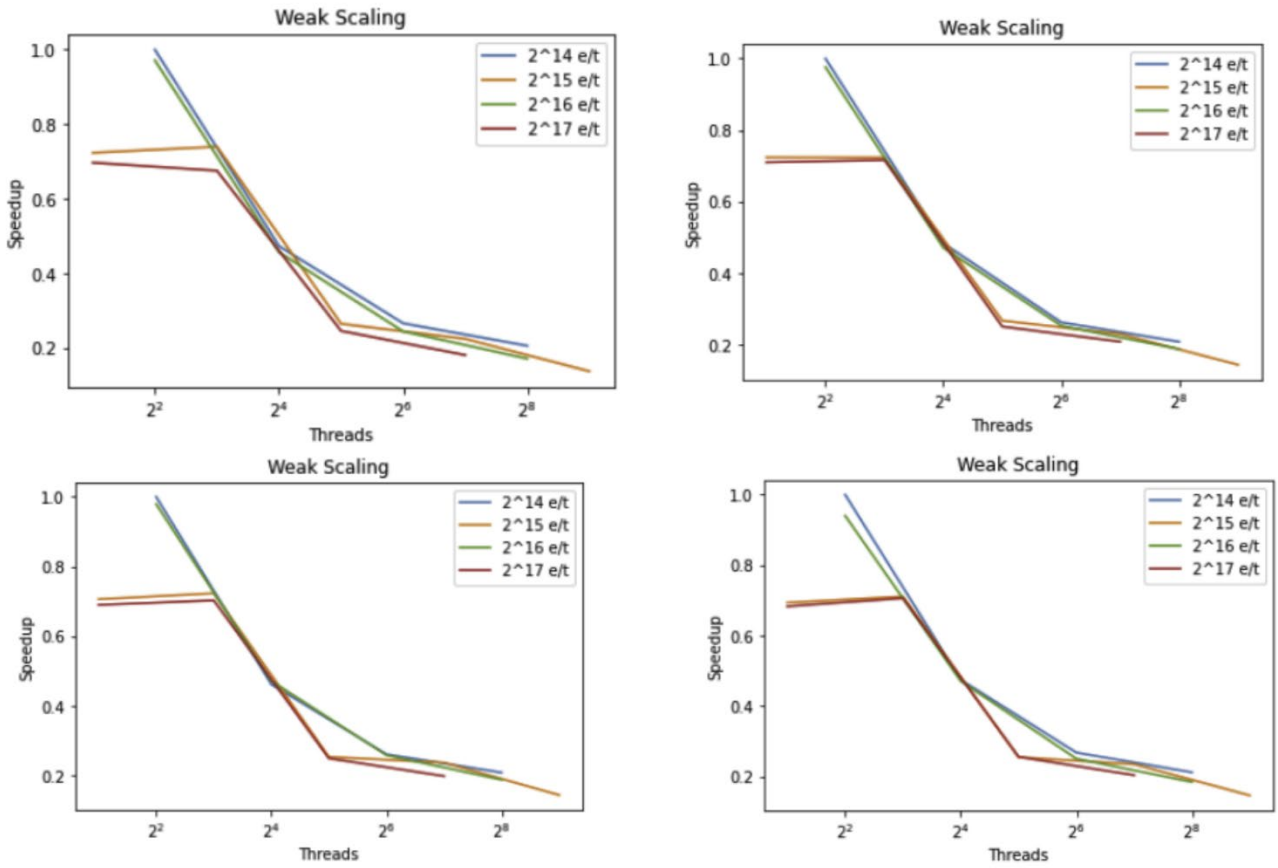
MPI Comparison between Input Types:

Strong Scaling:



From the graphs above we can see that the mpi implementation of quicksort did an awful job at parallelizing. For some of the array sizes it had a constant time meaning it didnt parallelize while for others it increased in time with the number of threads however we would have expected it to be decreasing. Quicksort is a sequential algorithm that we tried to parallelize but upon seeing the results we either should do a much better job or just not parallelize it at all. Overall, it seems like the mode affected the performance pretty low, but it seems like it performed the best/most consistently with random setting.

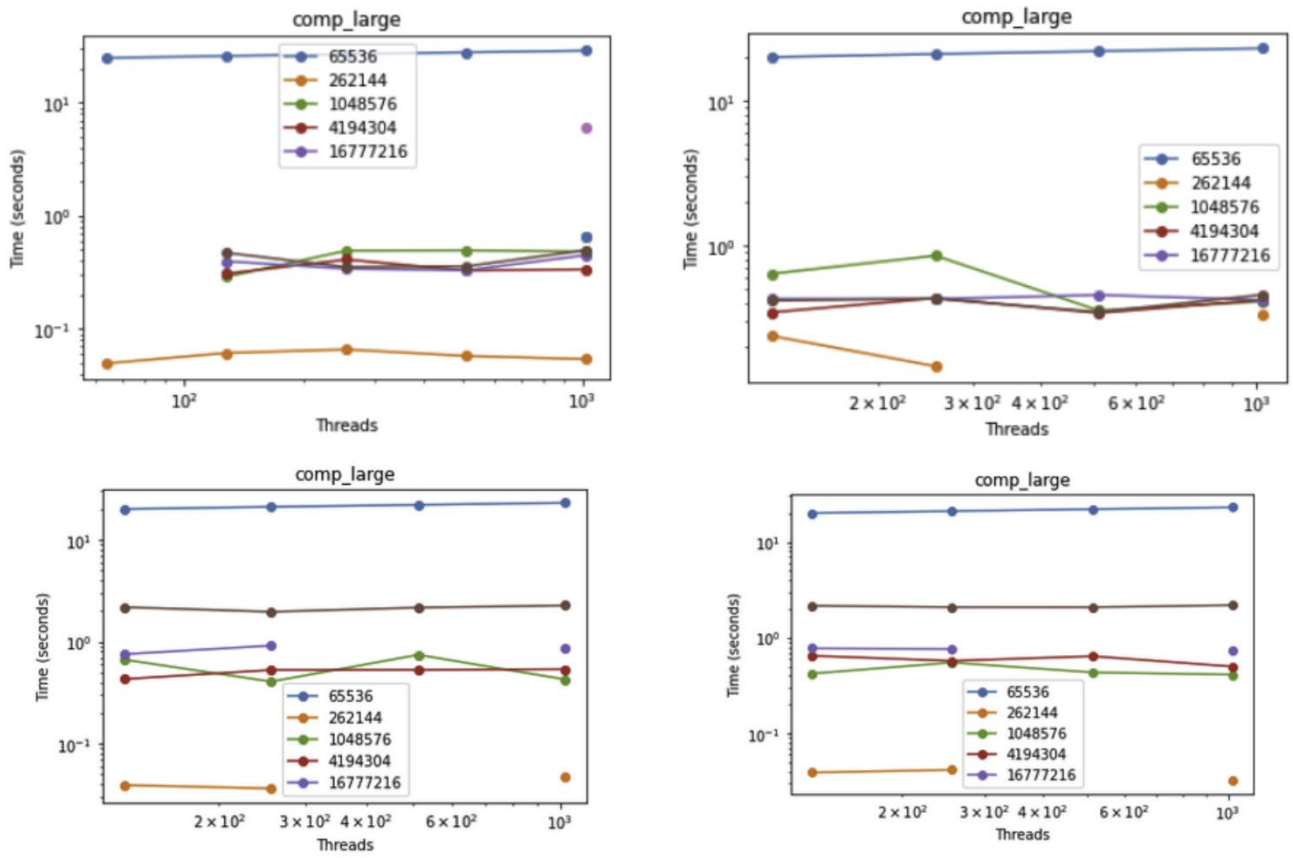
Weak Scaling:



As for weak scaling, again we see the opposite trend of what we would have expected, meaning the performance of the algorithm is just bad in general. There isn't much difference between the performance in terms of modes, so I don't think the mode made much difference in it.

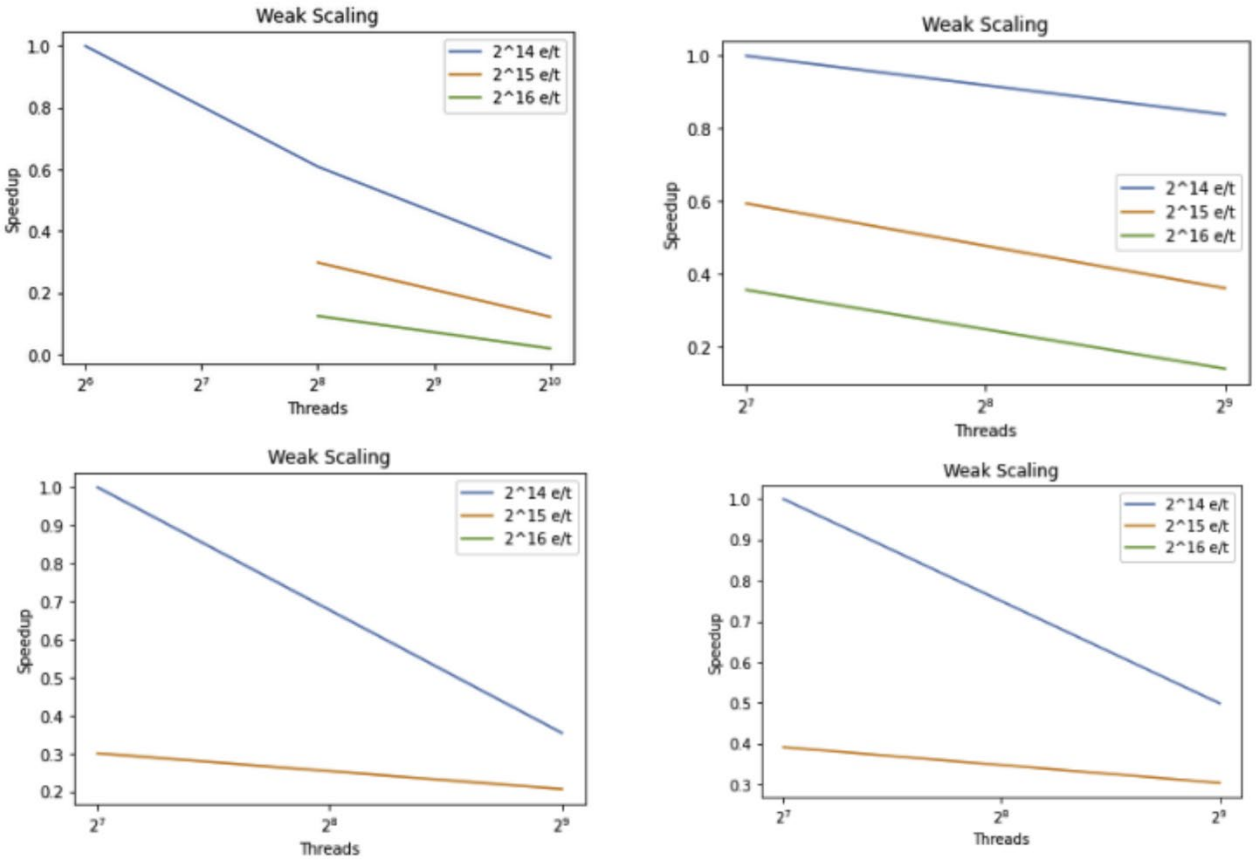
CUDA Comparison between Input Types:

Strong Scaling:



Overall, by looking at the strong scaling graphs it seems as though the program did not really parallelize. We would have expected the time to decrease as the number of threads increased, which would make sense, unfortunately that wasn't the case for our program. Upon comparing all 4 modes, it seems like mode 3 was the most consistent across all modes, leaving mode 1(top right) to be the most varying.

Weak Scaling:

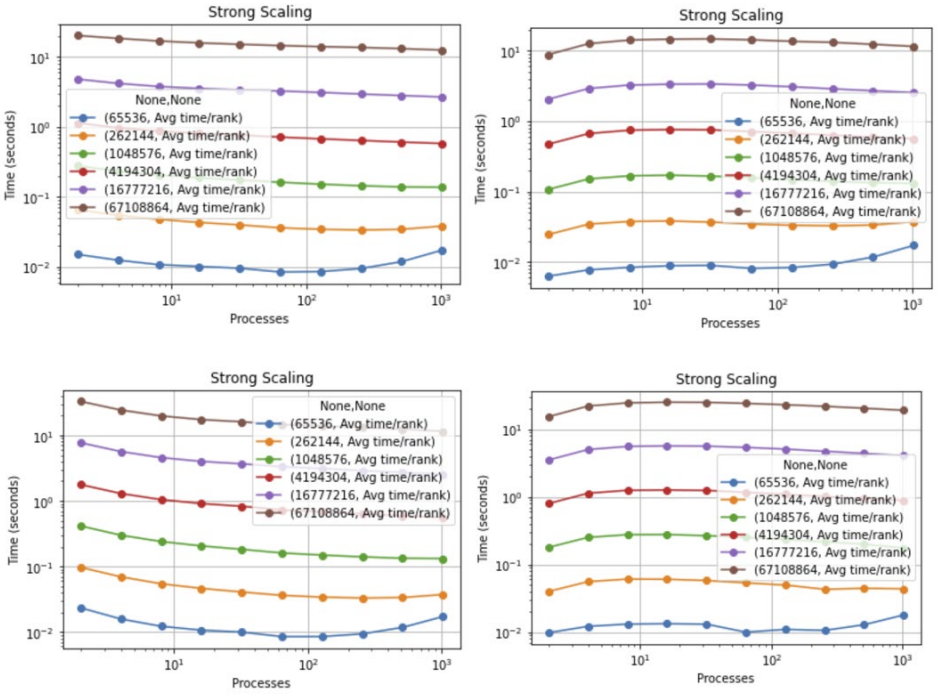


Again, as we saw in MPI implementation, weak scaling is just bad overall. We expected it to have a positive linear relationship but we mostly see a negative relationship between them or no relationship at all, my guess is best mode is 1(top right).

Bubble Sort:

MPI Comparison between Input Types:

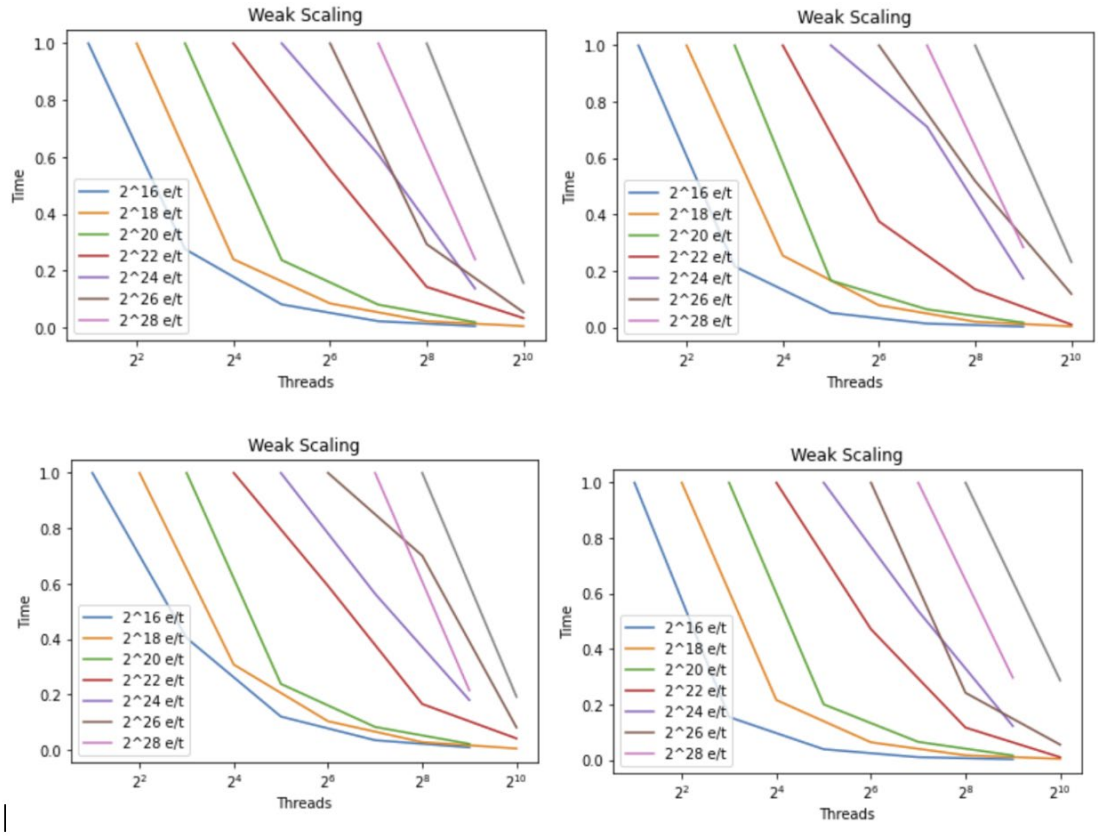
Strong Scaling:



Top left: Random Top Right: Sorted Bottom Left: Reverse Sorted Bottom Right: 1% Perturbed

From the 4 graphs, we can see that the random input type and 1% input type had the best strong scaling for the computation time. This is because of the fact that the bubble sort parallel implementation had to use an odd even transposition to make it parallelized. Odd even transposition works for higher input sizes which you can see that the time decreases as the input size increases. Additionally, due to the nature of odd even transposition, having a random input and 1% perturbed input is more efficient than a sorted or reverse sorted input.

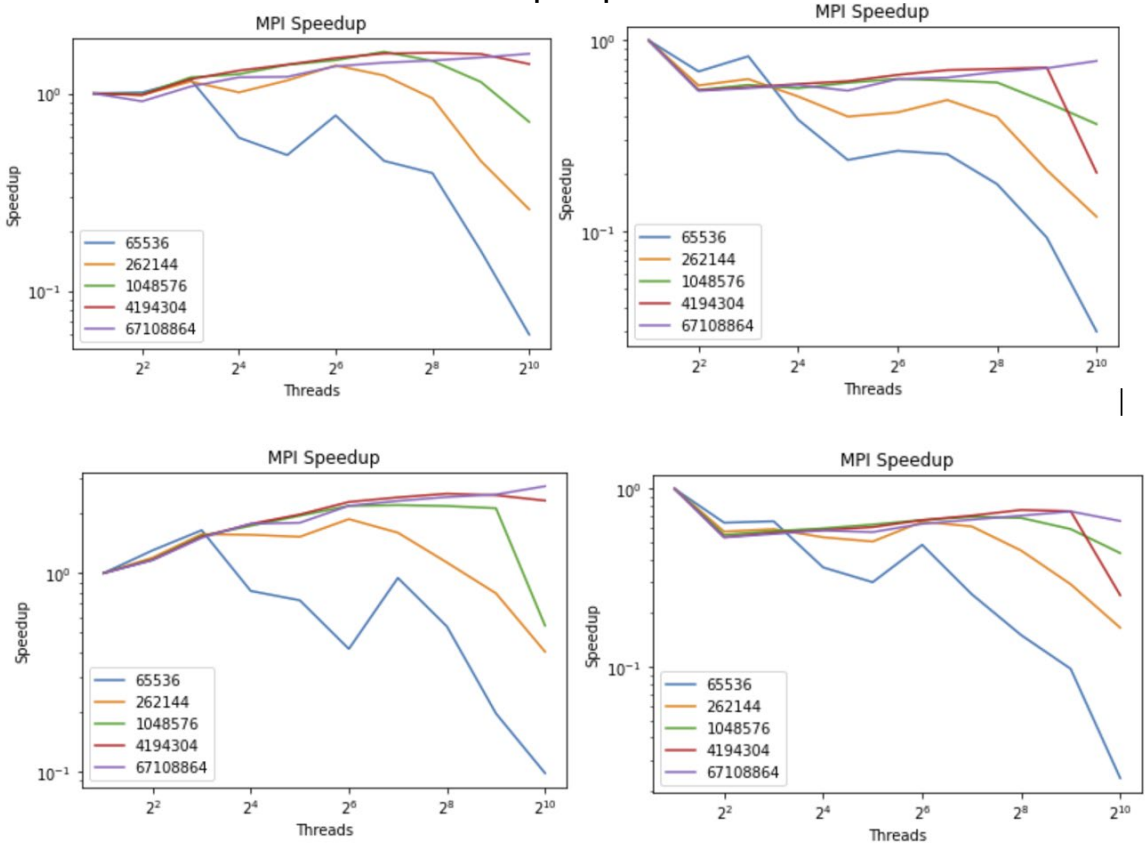
Weak Scaling:



Top left: Random Top Right: Sorted Bottom Left: Reverse Sorted Bottom Right: 1% Perturbed

From the 4 graphs, we can see that the main implementation of bubble sort scales weakly throughout all 4 input types. This is due to the fact that bubble sort itself is an extremely inefficient algorithm even with the help of an odd even transposition. This can also imply that the communication time was inefficient as well. Although the bubble sort implementation for MPI was parallelized, it was not parallelized well hence the weak scaling.

Speedup:



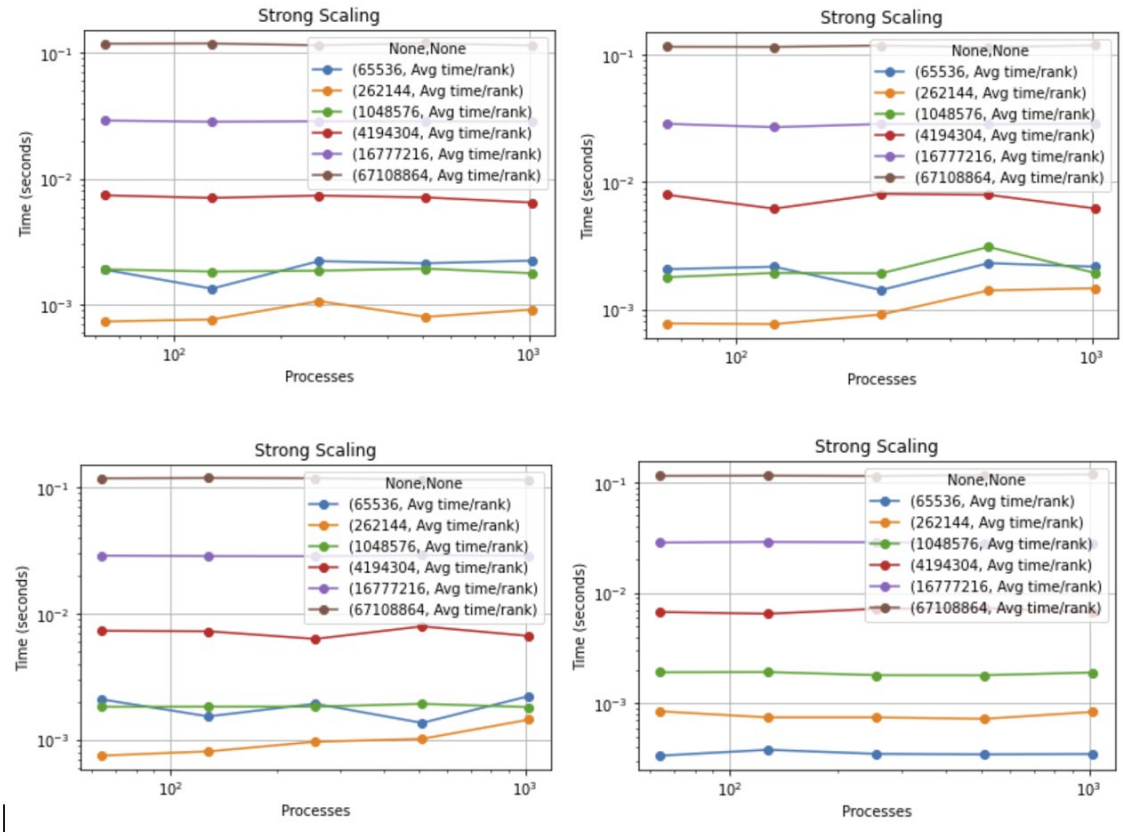
Top left: Random Top Right: Sorted Bottom Left: Reverse Sorted Bottom Right: 1% Perturbed

As seen from the 4 graphs, the speedup for each of the input type was not good, but out of the 4 data input types, the best speedup was the random input type. This is attributed to the fact that the odd even transposition works best with a random data than sorted or reverse sorted. However, since the implementation is still a bubble sort algorithm, the efficiency of the sorting gets worse if the data size is small.

Based on the analysis, the random input data performed the best which was expected given the behavior of odd even transposition, but due to the inherent inefficiency of bubble sort, it did not matter what kind of data type was used or what the data size was, leading it to still be pretty inefficient.

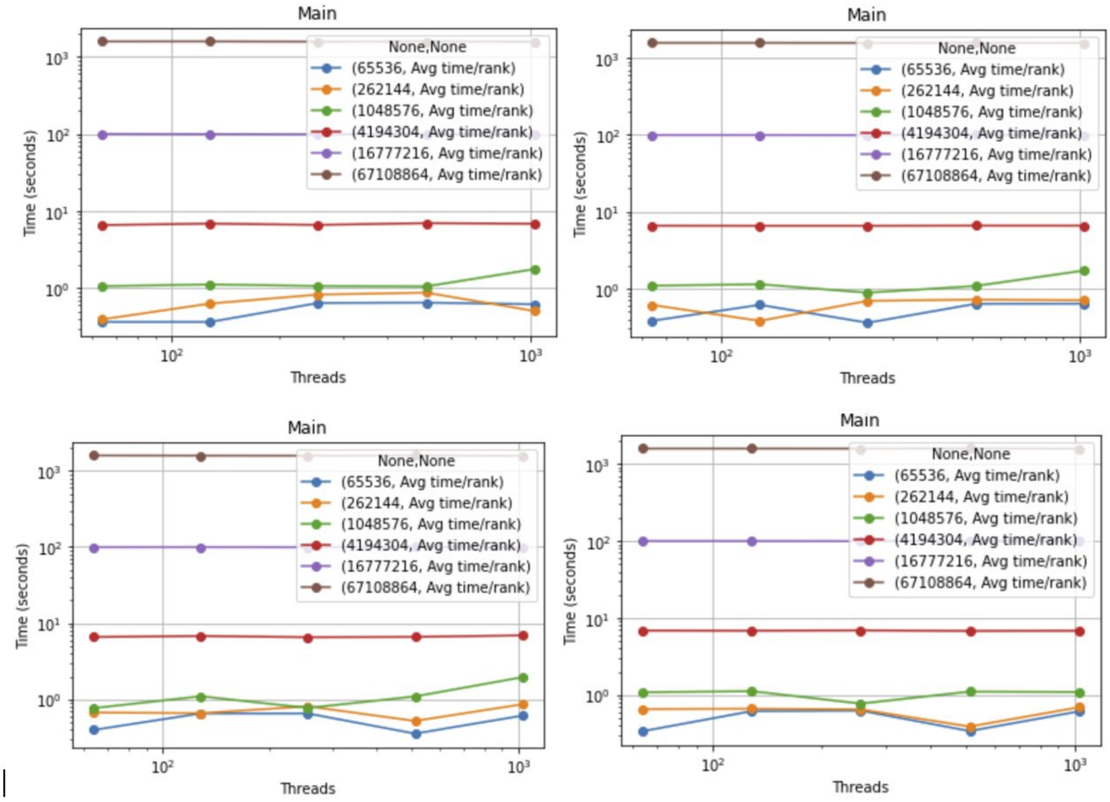
CUDA Comparison between Input Types:

Strong Scaling:



Top left: Random Top Right: Sorted Bottom Left: Reverse Sorted Bottom Right: 1% Perturbed

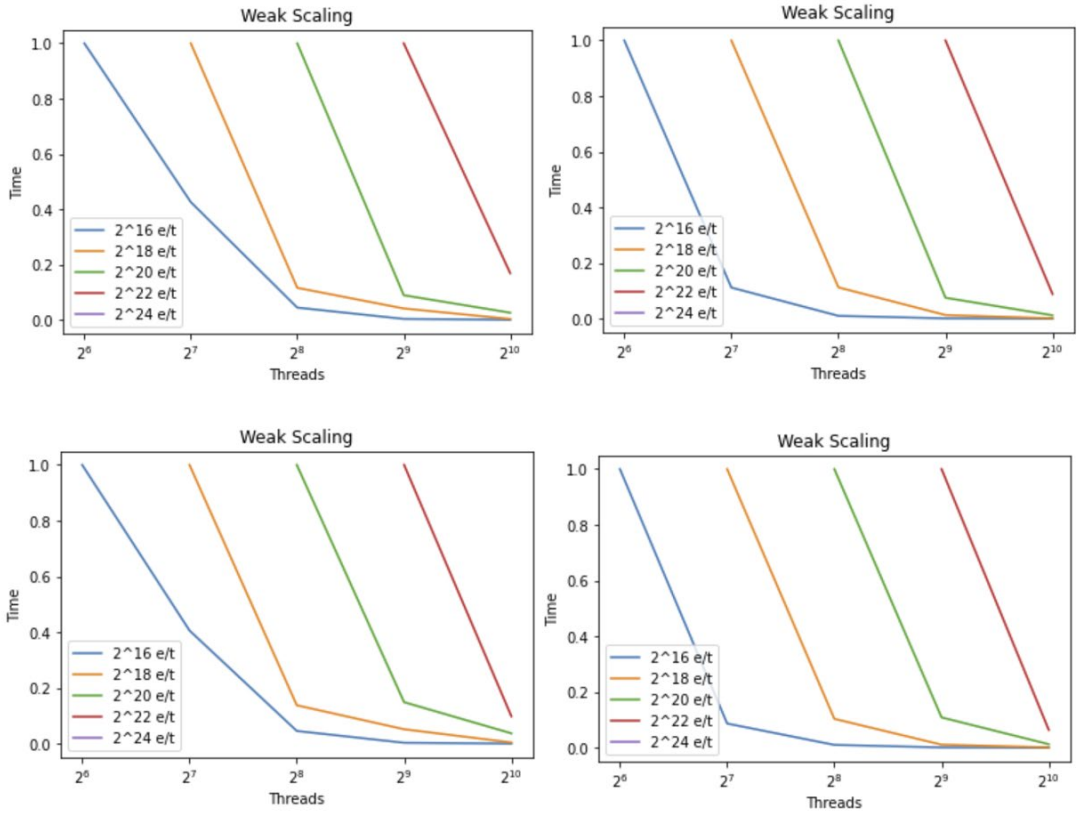
The CUDA implementation was not done well and in turn, it was parallelized very very inefficiently with extremely poor performance. As we can see from the 4 graphs, there is almost no strong scaling visible in the communication time for any of the data input types. I tried using the odd even transposition for the CUDA implementation as well and it was not parallelized well hence the extremely flat lines.



Top left: Random Top Right: Sorted Bottom Left: Reverse Sorted Bottom Right: 1% Perturbed

Similar to the communication graphs, the main graphs performance for main is poor with pretty flat lines throughout all 4 data input types. This is due to the fact that the CUDA implementation was done poorly in terms of parallelization.

Weak Scaling:



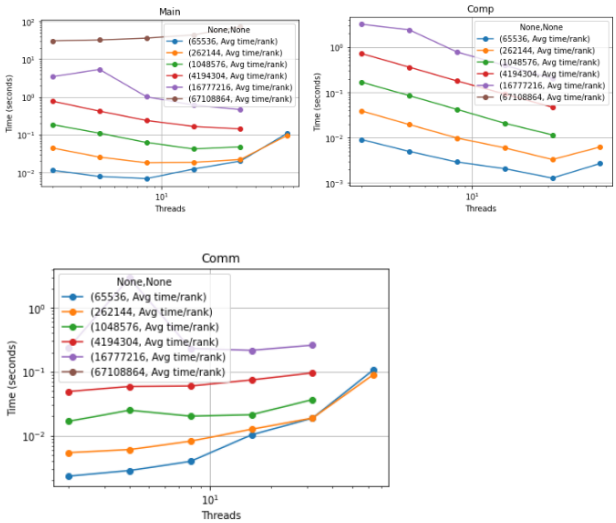
Top left: Random Top Right: Sorted Bottom Left: Reverse Sorted Bottom Right: 1% Perturbed As stated above, since the CUDA implementation was not parallelized well, there is a very weak scaling, but is almost not noticeable. There is almost no difference between the 4 data input types since they all perform poorly.

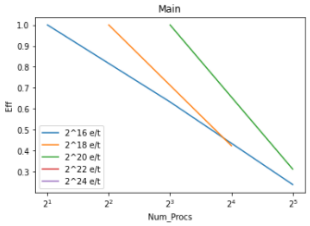
Based on the analysis, the CUDA implementation performed poorly throughout all the data input types. This is due to the fact that the CUDA implementation for bubble sort may not have been implemented correctly and/or implemented well and since bubble sort itself is inherently an inefficient algorithm, the performance would be poor no matter what the data type is.

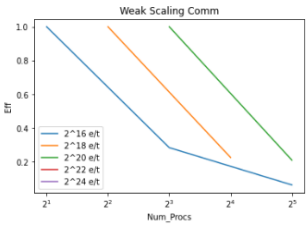
Sample Sort:

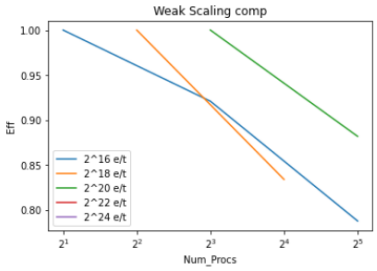
MPI Comparison:

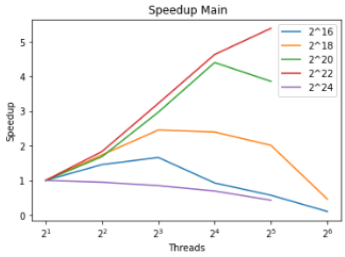
Random Input Data Type:

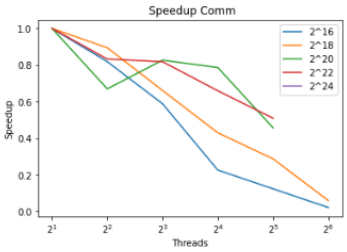


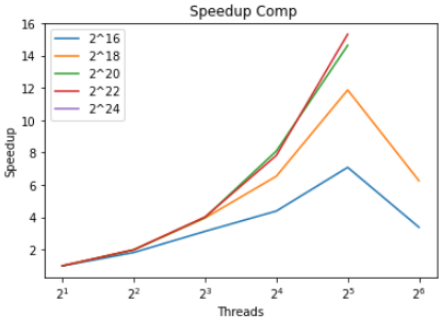

Main
Eff
Num_Procs
2^16 e/t
2^18 e/t
2^20 e/t
2^22 e/t
2^24 e/t


Weak Scaling Comm
Eff
Num_Procs
2^16 e/t
2^18 e/t
2^20 e/t
2^22 e/t
2^24 e/t

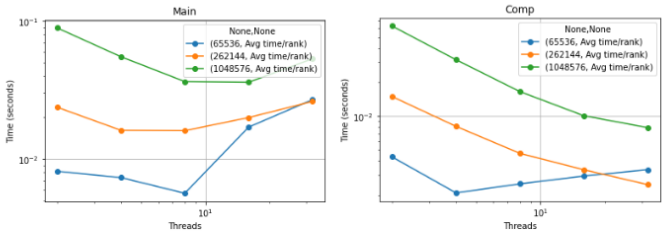

Weak Scaling comp
Eff
Num_Procs
2^16 e/t
2^18 e/t
2^20 e/t
2^22 e/t
2^24 e/t

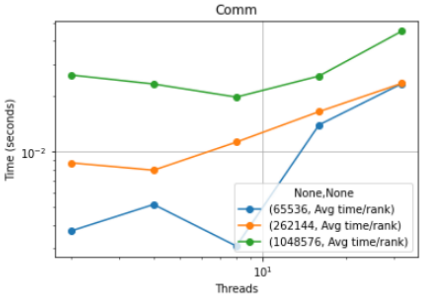

Speedup Main
Speedup
Threads
2^16
2^18
2^20
2^22
2^24

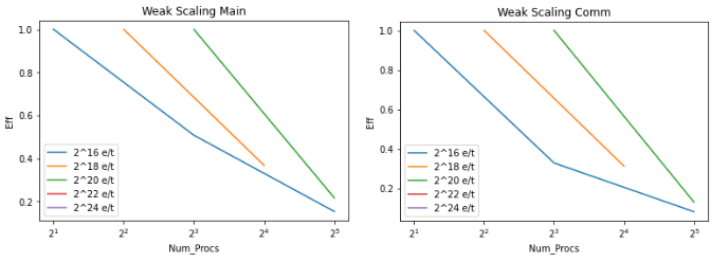

Speedup Comm
Speedup
Threads
2^16
2^18
2^20
2^22
2^24

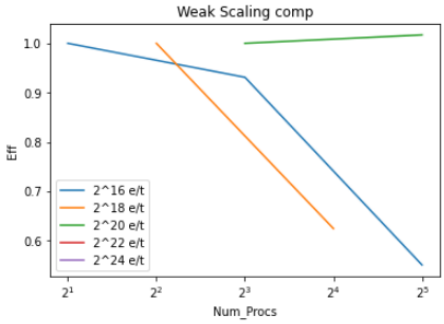

Speedup Comp
Speedup
Threads
2^16
2^18
2^20
2^22
2^24

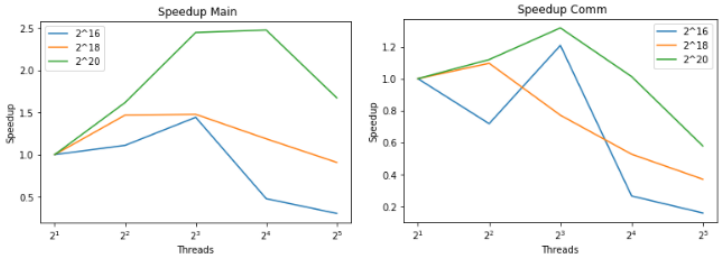
Sorted Input Data Type:

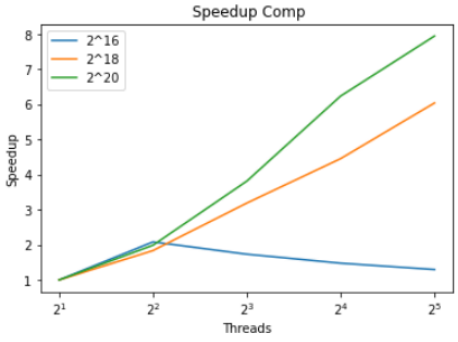




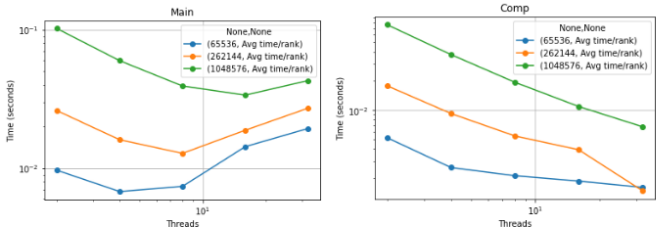


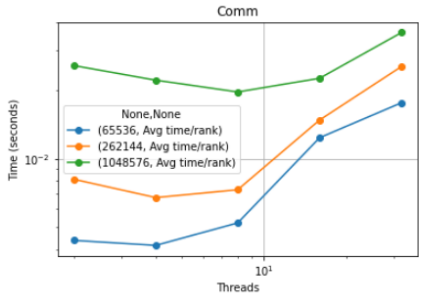


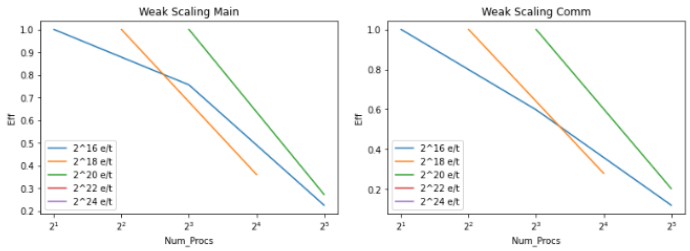


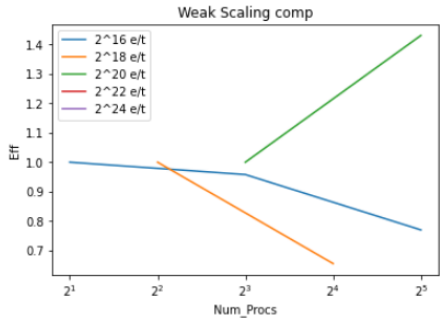


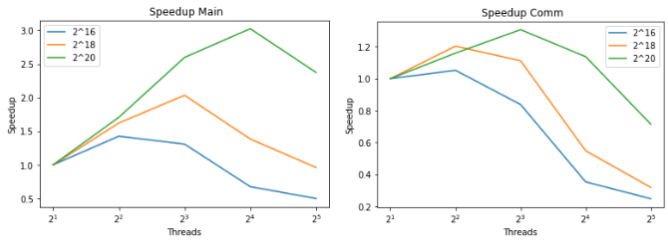
Reverse Sorted Input Data Type:

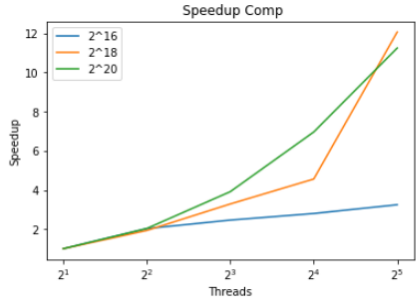




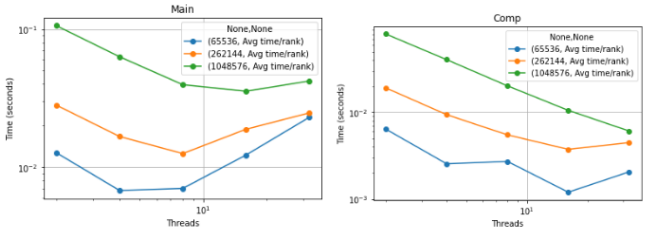


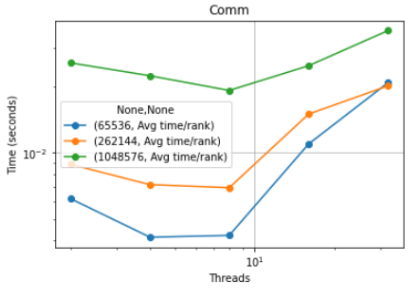


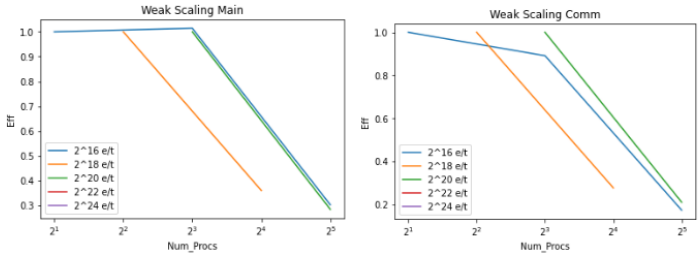


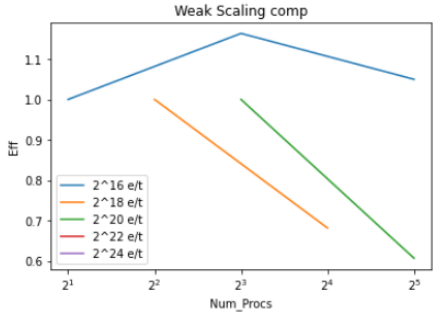


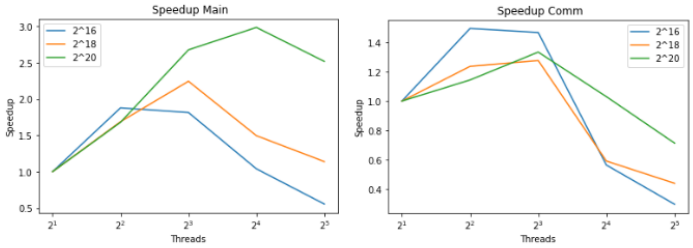
1% Perturbed Input Data Type:

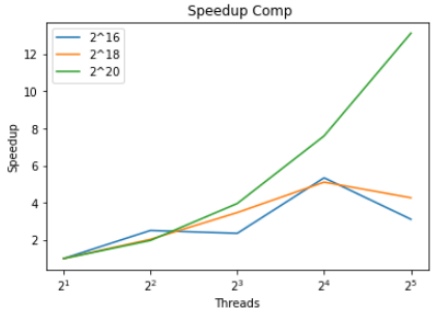












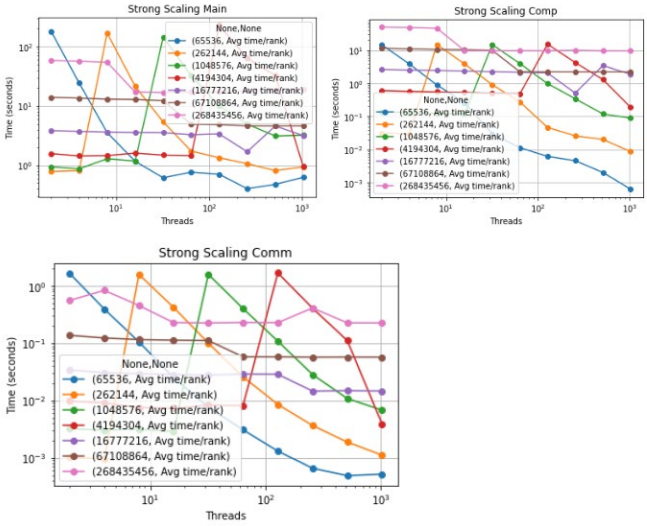
Analysis

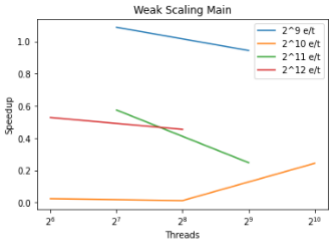
From all of these different graphs, one inference that can be made from the graph correlations is that additional number of processors decreases the computational time, but also increases the communication time. This makes sense, because the way parallel sample sort works, there is a lot of communication between processors to share splitters, and the processors also must communicate which bucket they will be sorting in which order. Likely, since there is also a lot of synchronization in the mpi sample sort, processors may end up having to wait for each other to finish. The decrease in computational time also makes sense, since the work is divided between processors. Each process takes a partition of the array to be sorted, locally sorts and eventually create global splitters. The processors then again take a specific bucket to be sorted and locally sorts their respective buckets, and then combines the buckets to finish the sort. More processors means more elements split into buckets for local sorting, which is why the computational time decreases as we increase processors.

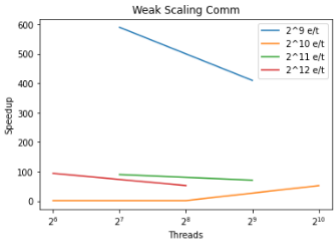
Another inference is that larger data sizes demonstrate a better correlation for the speedup of sample sort. This is likely due to the fact that for small input sizes, the work it takes to sort the array is so minimal that it isn't worth to add more processors since it would also increase the communication times between them. Furthermore, there is no significant difference between the times it take to sample sort for the different input types of sorted, random, reverse sorted, and one percent perturbed. This is likely due to the nature of sample sort, since it utilizes quick sort for local process sorting, the input type does not influence quick sort speed.

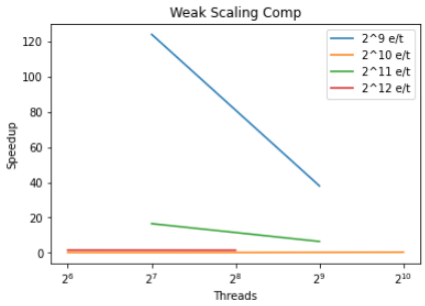
CUDA Comparison:

Random Input Data Type:

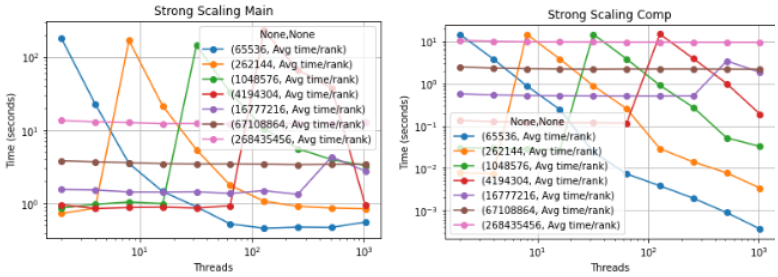


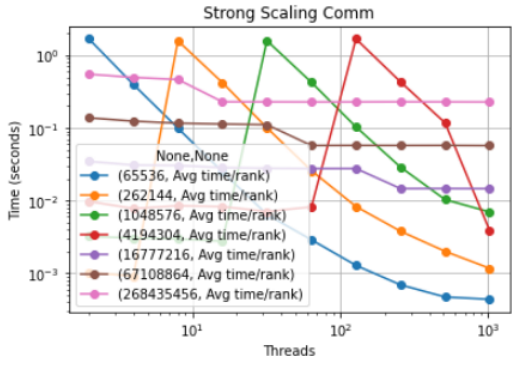


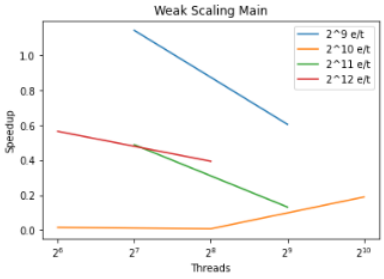


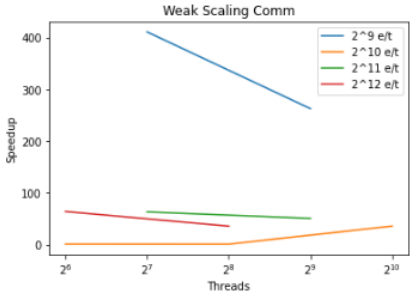


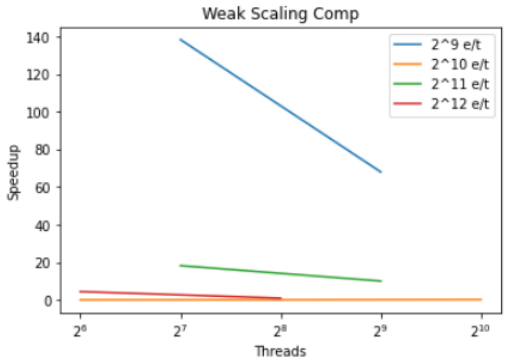
Sorted Input Data Type:



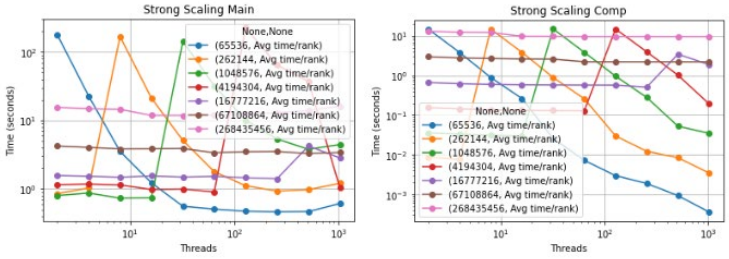


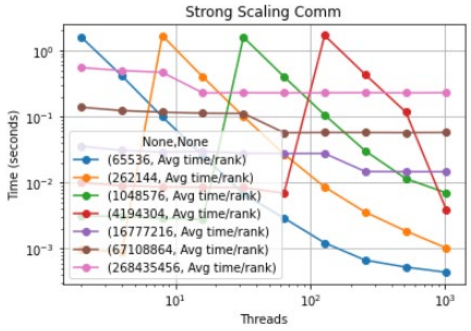


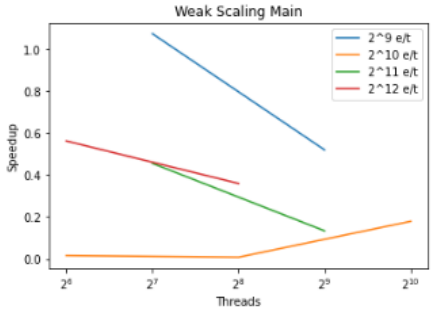


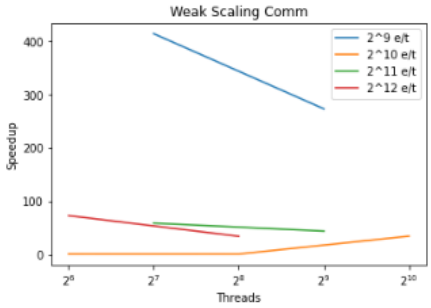


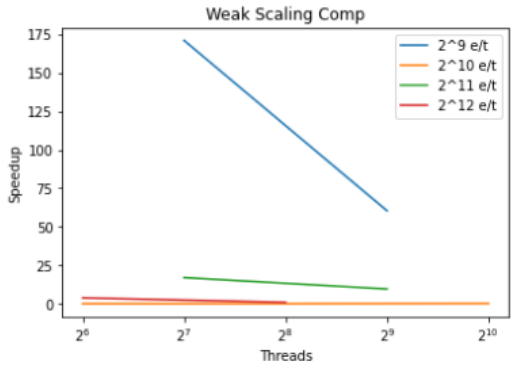
Reverse Sorted Input Data Type:


Strong Scaling Main
Time (seconds)
Threads
None,None
(65536, Avg time/rank)
(262144, Avg time/rank)
(1048576, Avg time/rank)
(4194304, Avg time/rank)
(16777216, Avg time/rank)
(67108864, Avg time/rank)
(268435456, Avg time/rank)
Strong Scaling Comp
Time (seconds)
Threads
None,None
(65536, Avg time/rank)
(262144, Avg time/rank)
(1048576, Avg time/rank)
(4194304, Avg time/rank)
(16777216, Avg time/rank)
(67108864, Avg time/rank)
(268435456, Avg time/rank)

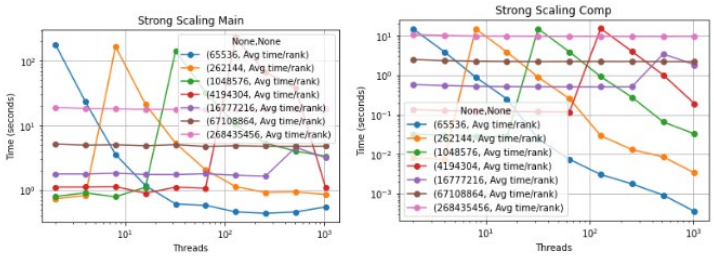

Strong Scaling Comm
Time (seconds)
Threads
None,None
(65536, Avg time/rank)
(262144, Avg time/rank)
(1048576, Avg time/rank)
(4194304, Avg time/rank)
(16777216, Avg time/rank)
(67108864, Avg time/rank)
(268435456, Avg time/rank)

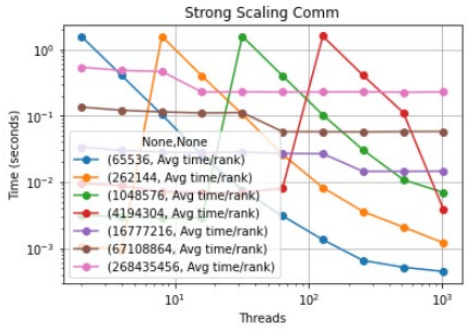

Weak Scaling Main
Speedup
Threads
2^9 e/t
2^10 e/t
2^11 e/t
2^12 e/t

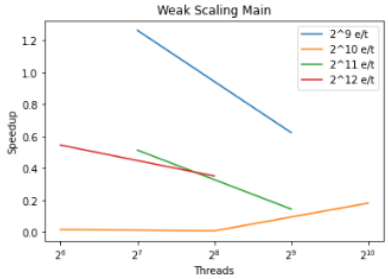

Weak Scaling Comm
Speedup
Threads
2^9 e/t
2^10 e/t
2^11 e/t
2^12 e/t

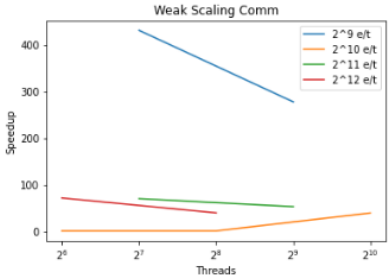

Weak Scaling Comp
Speedup
Threads
2^9 e/t
2^10 e/t
2^11 e/t
2^12 e/t

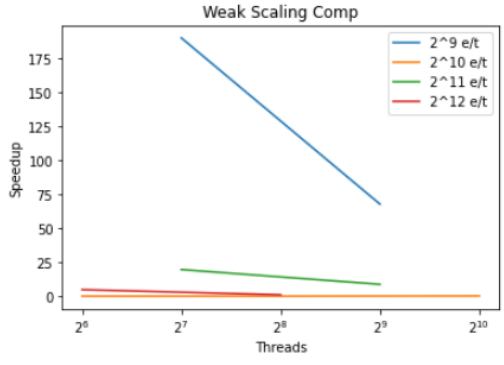
1% Perturbed Input Data Type:











Analysis

From the different graphs, there are no noticeable differences in sorting performance with different input types. Furthermore, the strong scaling graphs demonstrate that there is good parallelization for smaller input sizes, but struggles with larger input sizes. I don't really know why this is the case, but it looks like to me that maybe there weren't enough resources to allocate between threads for the larger input sizes. The weak scaling shows there is good parallelization for only the smallest input size. I think I should have tested even more smaller input sizes to make sure that this isn't just an outlier but that my code actually parallelizes for smaller input sizes.

4c Performance Metrics

- `Time`
  - Min time/rank
  - Max time/rank
  - Avg time/rank
  - Total time
  - Variance time/rank
  - `If GPU`:
    - Avg GPU time/rank
    - Min GPU time/rank
    - Max GPU time/rank
    - Total GPU time

The above performance metrics can be found in each of our own jupyter notebooks. Below is an example of the performance metrics for CUDA:

65536

node	num_threads	nid	spot.channel	Min time/rank	Max time/rank	Avg time/rank	Total time	Avg GPU time/rank	Min GPU time/rank	Max GPU time/rank	Total GPU time
{'name': 'main', 'type': 'function'}	2	1	regionprofile	178.807838	178.807838	178.807838	178.807838	163.613088	163.613088	163.613088	163.613088
	4	1	regionprofile	23.146228	23.146228	23.146228	23.146228	18.887782	18.887782	18.887782	18.887782
	8	1	regionprofile	3.549187	3.549187	3.549187	3.549187	2.319333	2.319333	2.319333	2.319333
	16	1	regionprofile	1.166638	1.166638	1.166638	1.166638	0.579781	0.579781	0.579781	0.579781
	32	1	regionprofile	0.607064	0.607064	0.607064	0.607064	0.228070	0.228070	0.228070	0.228070
	64	1	regionprofile	0.578610	0.578610	0.578610	0.578610	0.217549	0.217549	0.217549	0.217549
	128	1	regionprofile	0.458113	0.458113	0.458113	0.458113	0.124113	0.124113	0.124113	0.124113
	256	1	regionprofile	0.434332	0.434332	0.434332	0.434332	0.095010	0.095010	0.095010	0.095010