

## Binning in MPI and Cuda

### Method A

#### 4 Node Variable Classes

Nodes	# Elements	# Classes	Time
4	10,000	1	70 us
4	10,000	5	130 us
4	10,000	10	157 us
4	10,000	20	290 us
4	10,000	40	323 us

#### 8 Node Variable Classes

Nodes	# Elements	# Classes	Time
8	10,000	1	65 us
8	10,000	5	90 us
8	10,000	10	95 us
8	10,000	20	150 us
8	10,000	40	170 us

#### 8 Node Variable N

Nodes	# Elements	# Classes	Time
8	1000	5	35 us
8	10,000	5	95 us
8	100,000	5	571 us
8	1,000,000	5	5399 us
8	10,000,000	5	53,570 us
8	100,000,000	5	527,793 us

### Method B

#### 4 Node and 8 Node Variable N and

Nodes	# Elements	# Classes	Time
4	10,000	5	249 us

Nodes	# Elements	# Classes	Time
4	100,000	5	2179 us
8	10,000	5	204 us
8	100,000	5	2167 us

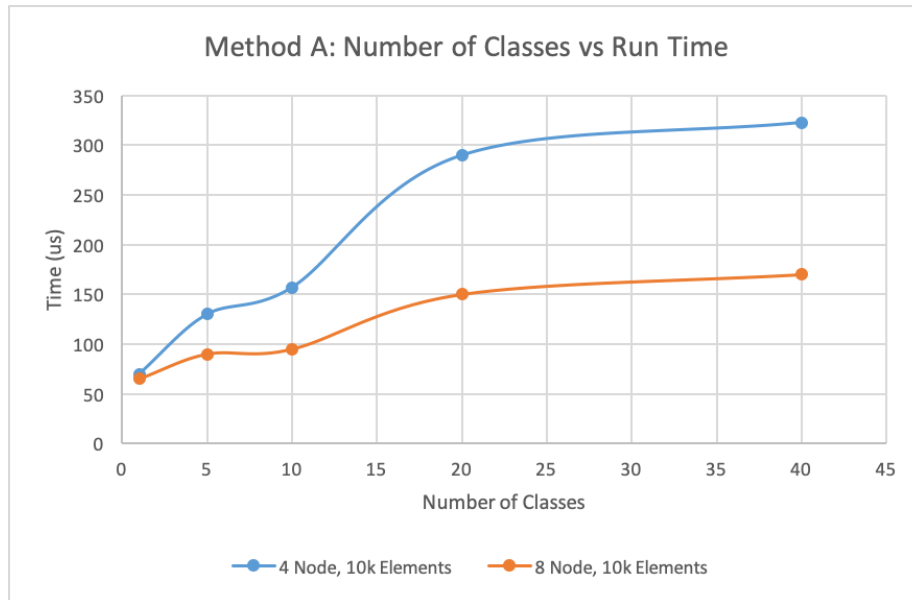
## Cuda A - Variable N

# Elements	# Classes	Run Time
10,000	5	252 us
100,000	5	300 us
1,000,000	5	400 us
10,000,000	5	448 us
100,000,000	5	651 us

## Analysis

Effect of...

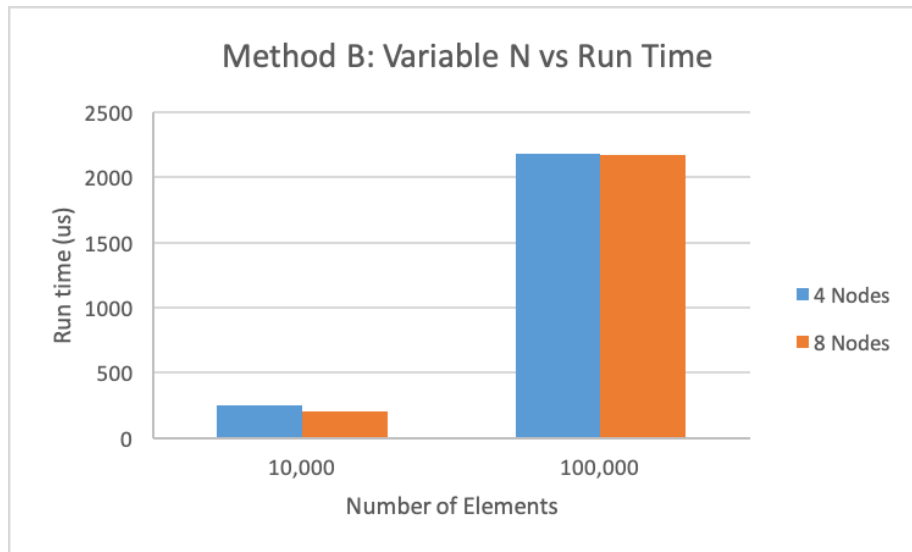
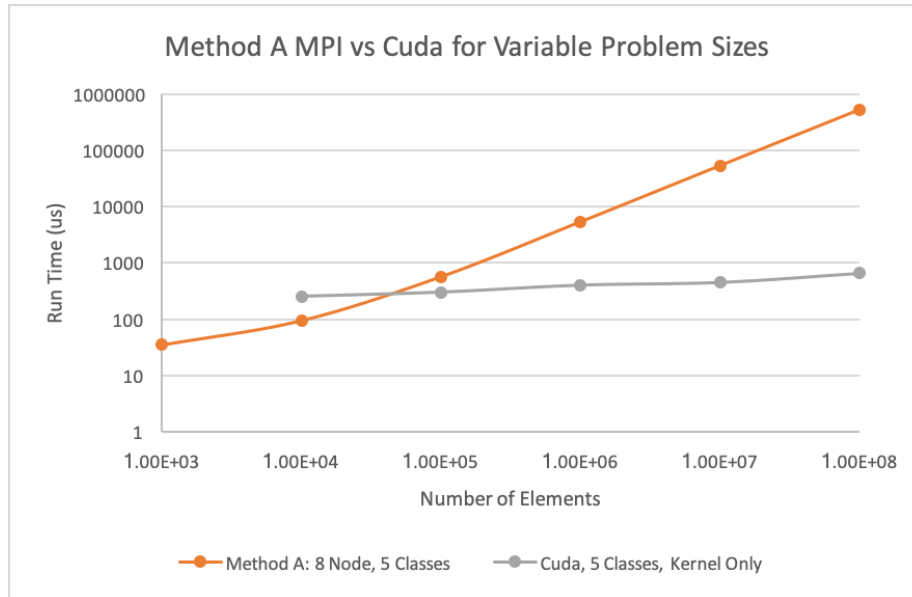
**Variable Classes:**



Demonstrated by the variable classes experiment run with method A. Having more classes resulted in long run times. There are two likely explanations for this: 1. With more classes, more comparisons must be made for each term

to find the correct bucket to place the value in 2. With more buckets to place the term in, the memory access pattern becomes even more complicated than before.

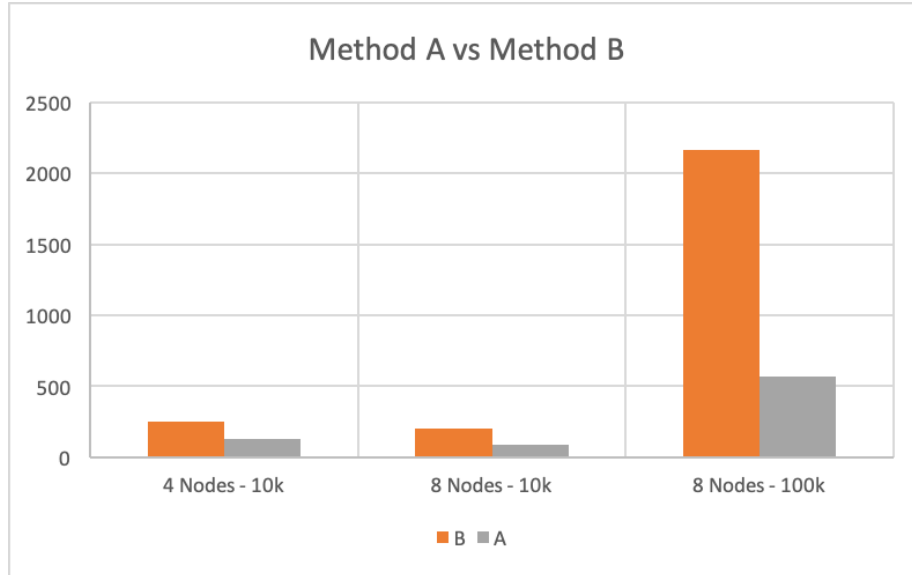
#### Variable Problem Size:



Demonstrated by the **8 Node Variable N** test case run with method A. With a larger N, the problem size grows and thus, we should expect the run time to grow as well. We see this behavior clearly in the the timing results. Initially,

an increase in problem size by a factor of 10 led to a small increase in run time, (less than an equivocal 10x increase in time). This is likely because the underlying hardware was being fully utilized in the smaller cases, thus increased problem sizes took advantage of idle hardware. However, the 10x jumps in problem size after 100,000 elements resulted in similar 10x jumps in the timing data.

#### Method A vs. Method B:

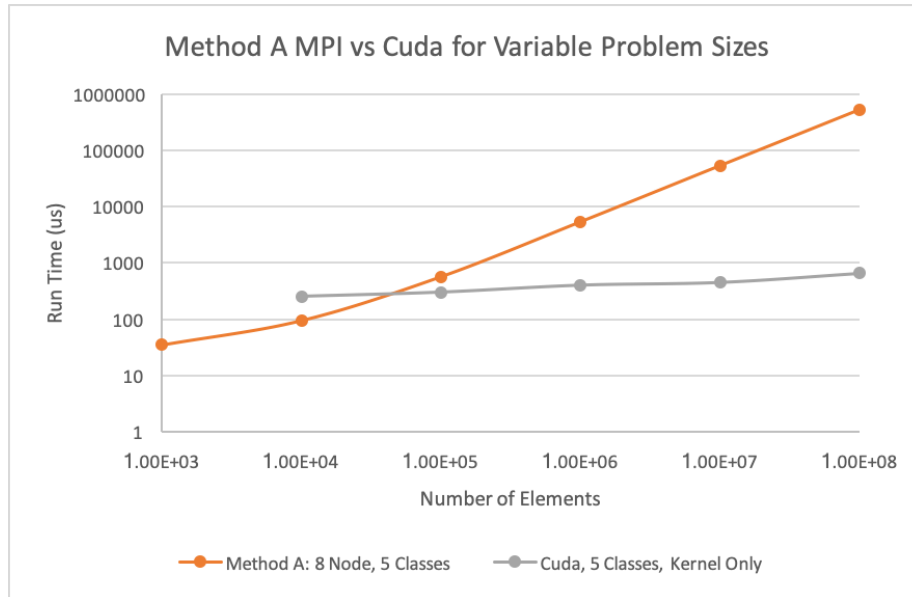


One of the most interesting questions to consider is how method A differs from the method B in timing.

In method A, a fraction of the data is read and completely sorted by each process. The end results are coalesced on node 0 at the end of the run time. In comparison, each node in method B reads the entire data stream and only pulls out nodes from a specific bucket type.

Our results show that method A is far superior to method B, in the 100k element case, running almost 4 times faster. This makes sense if we consider the how the algorithm is running. In method A, every piece of data is touched only once by any node before being sorted. Comparitively, in method B, each piece of data is touched by EVERY SINGLE NODE.

#### Method A vs. CUDA



Another highly interesting question to consider is how well a CUDA implementation of binning performs against the algorithm discussed in method A. Intuitively, the operations performed to "bin" data is very simple, simply determining where each piece of data falls within a set of buckets. We notice the run time remains fairly constant from problem size to problem size, while the run time from Method A increases linearly.

The following two images show an interesting result. In the first image, we see the profile data from a binning of 1000 elements. Here, we see the binning takes longer than the copy to the device. However as the problem size scales to 100,000,000 elements, we see that suddenly the memcpy takes a longer time, indicating that we've hit a memory bottleneck!

```
==2166== Profiling application: ./release/cuda_a
==2166== Profiling result:
```

Type	Time(%)	Time	Calls	Avg	Min	Max	Name
GPU activities:	50.91%	3.5840us	1	3.5840us	3.5840us	3.5840us	bin(int*, int*, int, int, int)
	26.82%	1.8880us	1	1.8880us	1.8880us	1.8880us	[CUDA memcpy HtoD]
	22.27%	1.5680us	1	1.5680us	1.5680us	1.5680us	[CUDA memcpy DtoH]
API calls:	99.49%	213.49ms	2	106.75ms	197.03us	213.30ms	cudaMalloc
	0.28%	601.89us	94	6.4030us	307ns	256.52us	cuDeviceGetAttribute
	0.08%	181.93us	1	181.93us	181.93us	181.93us	cuDeviceTotalMem
	0.07%	157.39us	1	157.39us	157.39us	157.39us	cudaLaunch
	0.03%	68.817us	2	34.408us	33.179us	35.638us	cudaMemcpy
	0.03%	62.229us	1	62.229us	62.229us	62.229us	cuDeviceGetName
	0.00%	8.7240us	5	1.7440us	165ns	6.9370us	cudaSetupArgument
	0.00%	4.7580us	3	1.5860us	417ns	2.8730us	cuDeviceGetCount
	0.00%	2.7400us	2	1.3700us	517ns	2.2230us	cuDeviceGet
	0.00%	1.6870us	1	1.6870us	1.6870us	1.6870us	cudaConfigureCall

```
==2693== Profiling application: ./release/cuda_a
==2693== Profiling result:
```

Line #	Pascal Type	Time(%)	V100 Time	Calls	Avg	Min	Max	Name
GPU activities:		74.62%	126.35ms	1	126.35ms	126.35ms	126.35ms	[CUDA memcpy HtoD]
16	NVLink: 160 GB/s	25.38%	42.976ms	GPU to 1	42.976ms	42.976ms	42.976ms	bin(int*, int*, int, int, int)
17	HBM2: "Stacked High Bandwidth Memory"	0.01%	8.8320us	Memory 1	8.8320us	8.8320us	8.8320us	[CUDA memcpy DtoH]
18	API calls: none	52.48%	188.45ms	memory 2	94.224ms	183.64us	188.26ms	cudaMalloc
19	Preemptive compute	47.29%	169.82ms	compute 2	84.908ms	42.930ms	126.89ms	cudaMemcpy
20	at the instruction level	0.11%	412.37us	94	4.3860us	176ns	169.61us	cuDeviceGetAttribute
21	16nm FinFET	0.06%	215.39us	1	215.39us	215.39us	215.39us	cudaLaunch
22	Uses SM and CUDA Cores	0.03%	109.68us	1	109.68us	109.68us	109.68us	cuDeviceTotalMem
23	Uses FP16 instead of the more widely used FP32/FP64	0.01%	41.106us	widely 1	41.106us	41.106us	41.106us	cuDeviceGetName
24	increases accuracy	0.01%	18.450us	very high 5	3.6900us	155ns	10.085us	cudaSetupArgument
25	**Goal: greatly increase memory bandwidth and reduce communication overheads to improve throughput	0.00%	3.6630us	bandwidth 1	3.6630us	3.6630us	3.6630us	cudaConfigureCall
26	improve throughput	0.00%	2.8000us	3	933ns	244ns	1.7070us	cuDeviceGetCount
27		0.00%	1.7480us	2	874ns	299ns	1.4490us	cuDeviceGet

## Pascal P100 vs Volta V100

Pascal:

- NVLink: 160 GB/s bidirectional GPU to GPU communication
- HBM2: "Stacked High Bandwidth Memory"
- Unified Memory: single virtual memory space for CPU and GPU
- Preemptive compute: preemptive compute allows instructions to be interrupted at the instruction level
- 16nm FinFET
- Uses SM and CUDA Cores
- Uses FP16 instead of the more widely used FP32/FP64 - doubles performance and increases accuracy (don't want very high precision values for deep learning)
- **Goal: greatly increase memory bandwidth and reduce communication overheads to improve throughput**

V100:

- Introduction of Tensor Cores alongside CUDA Cores
- Targeted towards DL/ML
- Larger L1 Cache than the P100
- V100: unified shared memory/L1 cache
  - low cache hit latency
- Independent thread scheduling allows for in-warp synchronization
- **Tensor cores** offers multiply and add operations for greater efficiency breaks away from the P100 focus on SM/CUDA cores
- improved unified memory
- improved HBM2 and NVLink performance
- **Goal: EXTREME performance on deep learning applications.**

EC



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==2032== Profiling application: ./sobel input/leopard.jpg edge.jpg
==2032== Profiling result:
   Type      Time(%)      Time      Calls      Avg      Min      Max      Name
GPU activities:
42.49% 525.42us 1 525.42us 525.42us 525.42us [CUDA memcpy DtoH]
42.01% 519.56us 1 519.56us 519.56us 519.56us [CUDA memcpy HtoD]
15.41% 190.63us 1 190.63us 190.63us 190.63us kernel(unsigned char*, unsigned char*, unsigned int, unsigned int)
0.09% 1.0880us 1 1.0880us 1.0880us 1.0880us [CUDA memset]
API calls:
98.31% 203.96ms 2 101.98ms 203.43us 203.75ms cudaMalloc
0.79% 1.6477ms 2 823.83us 717.48us 930.18us cudaMemcpy
0.32% 667.71us 94 7.1030us 327ns 229.21us cuDeviceGetAttribute
0.24% 487.65us 2 243.83us 166.32us 321.33us cudaFree
0.16% 326.42us 2 163.21us 135.02us 191.40us cuDeviceSynchronize
0.09% 197.01us 1 197.01us 197.01us 197.01us cuDeviceTotalMem
0.03% 68.786us 1 68.786us 68.786us 68.786us cuDeviceGetName
0.03% 58.389us 1 58.389us 58.389us 58.389us cudaMemset
0.01% 31.068us 1 31.068us 31.068us 31.068us cudaLaunch
0.00% 4.9710us 3 1.6570us 403ns 2.9800us cuDeviceGetCount
0.00% 3.4150us 2 1.7070us 605ns 2.8100us cuDeviceGet
0.00% 2.5690us 4 642ns 165ns 1.4330us cudaSetupArgument
0.00% 1.6010us 1 1.6010us 1.6010us 1.6010us cudaConfigureCall
0.00% 547ns 1 547ns 547ns 547ns cudaPeekAtLastError

```