Assignment 3

Felix Söderman DD2360 HT23
Github: https://github.com/felixcool200/DD2360HT23

Exercise 1 - Your first CUDA program and GPU performance metrics

1. Explain how the program is compiled and run.

   ANSWER: To compile the program use the created a make file that executes the following command:

   `nvcc -arch=sm_61 vecto`.cu -o a.out`

2. For a vector length of N:

   1. How many floating operations are being performed in your vector add kernel?

      ANSWER: When adding a two vectors of length N there are N plus floating point operations that are performed.

   2. How many global memory reads are being performed by your kernel?

      ANSWER: Since both vectors are read once for each addition there is a total of 2N reads from global memory.

3. For a vector length of 1024:

   1. Explain how many CUDA threads and thread blocks you used.

      ANSWER: I used (1024+32-1)/32 = 32 thread blocks. and I used 32*32=1024 CUDA threads.

   2. Profile your program with Nvidia Nsight. What Achieved Occupancy did you get?

      ANSWER: I got Achieved Occupancy of 3.12% and a Theoretical Occupancy of 50%.

      When incresing the threads per block from 32 to 64 the Theoretical Occupancy increesed to 100% and the Achieved Occupancy to 6.19%

4. Now increase the vector length to 131070:

   1. Did your program still work? If not, what changes did you make?

      ANSWER: The program still works. No changes needed to be made.

   2. Explain how many CUDA threads and thread blocks you used.

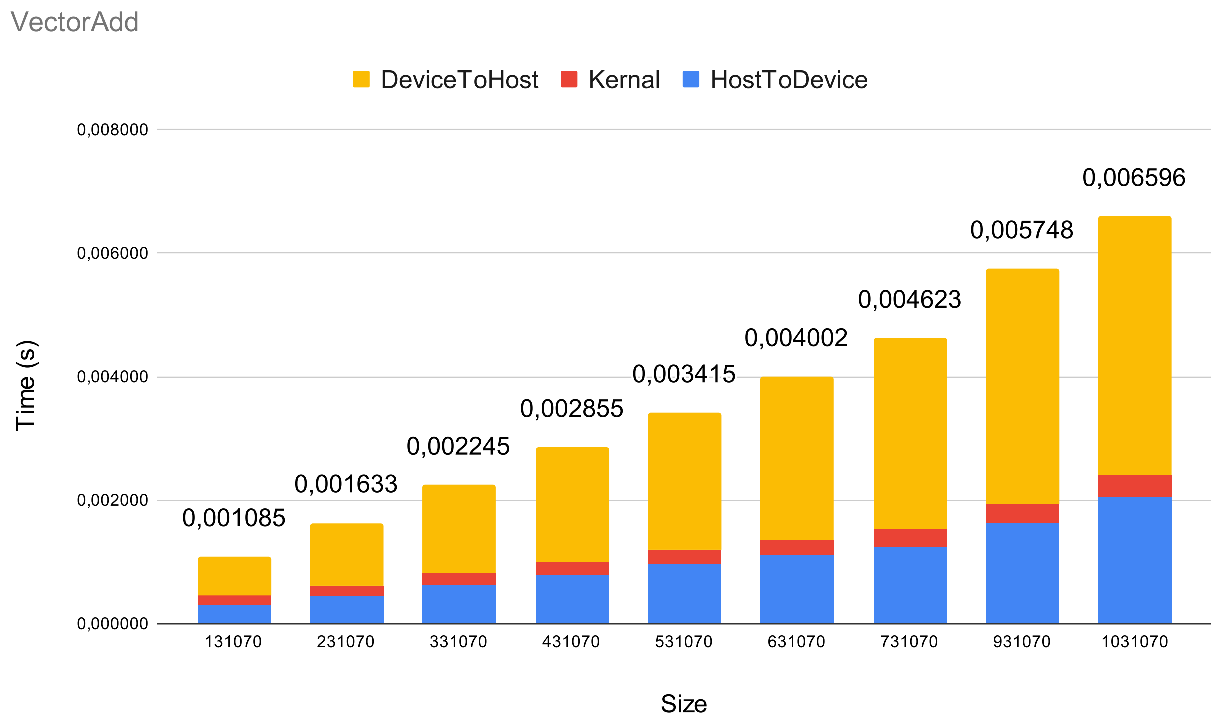
      ANSWER: I used (131070+32-1)/32 = 4096 thread blocks. and I used 4096*32 = 131072 CUDA threads.

   3. Profile your program with Nvidia Nsight. What Achieved Occupancy do you get now?

      ANSWER: Achieved Occupancy is now 32.57% (at TPB at 32) and 74.35% (at TPB at 64)

5. Further increase the vector length (try 6-10 different vector length), plot a stacked bar chart showing the breakdown of time including (1) data copy from host to device (2) the CUDA kernel (3) data copy from device to host. For this, you will need to add simple CPU timers to your code regions.

   ANSWER:



Exercise 2 - Your first CUDA program and GPU performance metrics

1. Name three applications domains of matrix multiplication.

   ANSWER: One application is machine learning, where matrix multiplication forms the foundation for training models. This is why tensor cores are specifically developed for performing matrix multiplications.

   Another application is solving linear equation systems, which is essential in engineering, as many systems can be modeled as a linear combination of variables.

   Lastly, in game programming, matrix multiplication can be used to rotate objects in 3D space, often employing rotation matrices.

2. How many floating operations are being performed in your matrix multiply kernel?

   ANSWER: I have written three different implementation of my kernal. The one using atomicAdd runs 2 floating point operation (per thread), one for multiplying the values and one for atomicadd to the C vector.

   While the second runs first a two floating point operation (similar to the last one, but add to shared variable instead of atomicAdd), but if it is threadIdx.x = 0 it also does numAColumns additional floating point operations when taking the sum over the shared variable.

   Lastly my last kernal always runs numAColumns floating point operations (per thread).

When talking about an entire run we multiply the number from the previous question with how many threads are created. Which is equal to the amount of numCRows * numCColumns for the first and third kernal implementation but for the second one there is numCRows * numCColumns * numAColumns since it runs all calculations in paralell.

(I added a table at the end of question 3 to show all values)

3. How many global memory reads are being performed by your kernel?

   ANSWER: All three versions of my kernals only read the global memory twice.

Kernal	gemmShared	gemmAtomicAdd	gemmBIG
Number of threads (excluding CUDA threads that do no global memory reads and no floating point operations)	numCColumns * numCRows * numAColumns	numCColumns * numCRows * numAColumns	numCColumns * numCRows
Number of floating point operations (per thread)	2 or 2+numAColumns	2	2*numAColumns
Global memory reads (per thread)	2	2	2*numAColumns
Number of floating point operations (total)	(2 or 2+numAColumns) * numCColumns * numCRows * numAColumns	2 * numCColumns * numCRows * numAColumns	2 * numAColumns * numCColumns * numCRows
Global memory reads (total)	2 * numCColumns * numCRows * numAColumns	2 * numCColumns * numCRows * numAColumns	2 * numAColumns * numCColumns * numCRows

4. For a matrix A of (128x128) and B of (128x128):

   1. Explain how many CUDA threads and thread blocks you used.

      ANSWER: For the first and second kernal implementation there is numCRows * numCColumns * numAColumns which results in 128^3 = 2097152 CUDA threads

      For the third kernal implementation there are numCRows * numCColumns kernals which means that in this case it is 128^2 = 16384 CUDA threads.

   2. Profile your program with Nvidia Nsight. What Achieved Occupancy did you get?

      ANSWER:

Kernal	gemmShared	gemmAtomicAdd	gemmBIG
Cuda threads	2097152	2097152	16384

Kernal	gemmShared	gemmAtomicAdd	gemmBIG
Achieved occupancy (%)	88.35	88.55	98.15

5. For a matrix A of (511x1023) and B of (1023x4094):

    1. Did your program still work? If not, what changes did you make?

        ANSWER: This workes for all three of my kernal versions (first and second kernal does not allow for 1023 to go above 1024, since that would need more than 1024 threads per block which is not possible).

    2. Explain how many CUDA threads and thread blocks you used.

        ANSWER: For the first and second kernal implementation there is numCRows * numCColumns * numAColumns which results in 511 * 4094 * 1023 = 2140150782 CUDA threads

        For the third kernal implementation there are numCRows * numCColumns kernals which means that in this case it is 511 * 4094 = 2092034 CUDA threads.

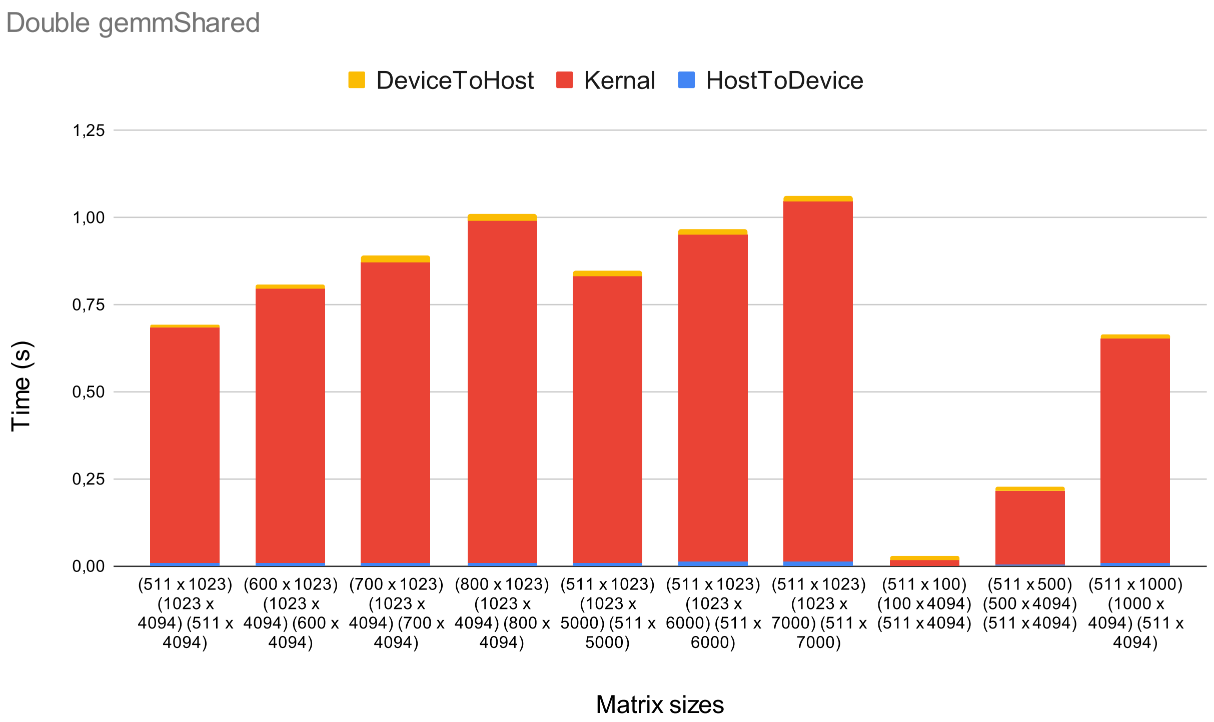
    3. Profile your program with Nvidia Nsight. What Achieved Occupancy do you get now?

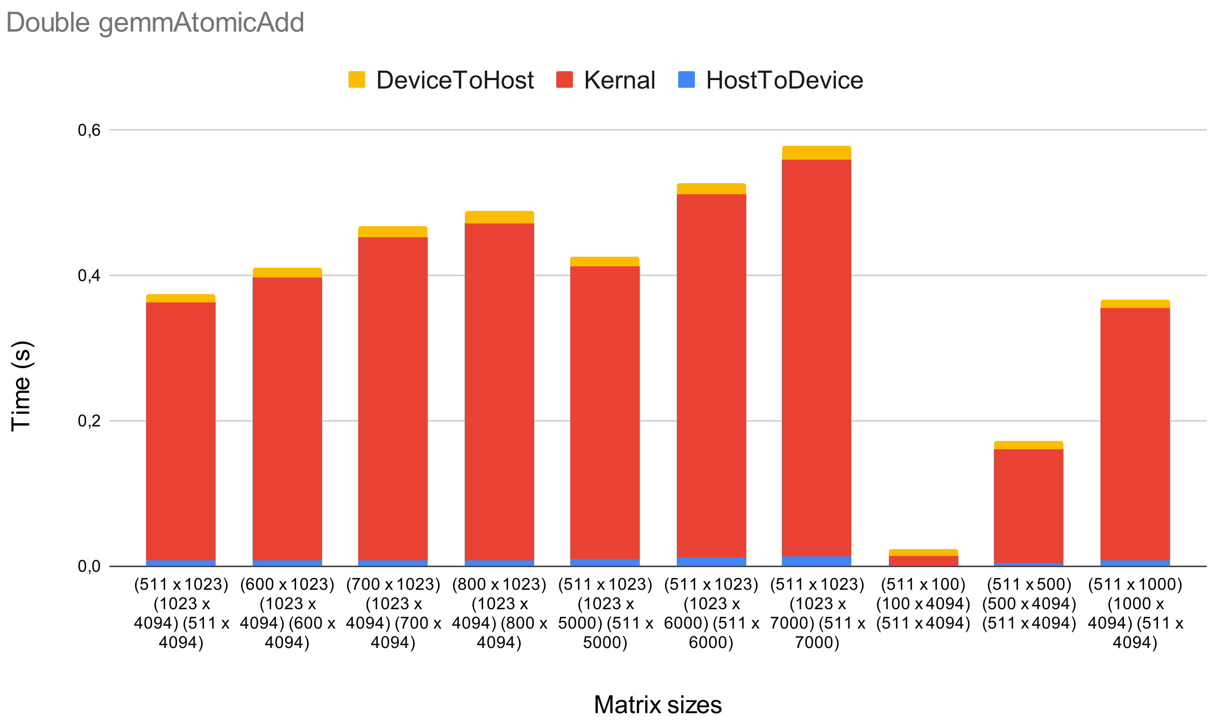
        ANSWER:

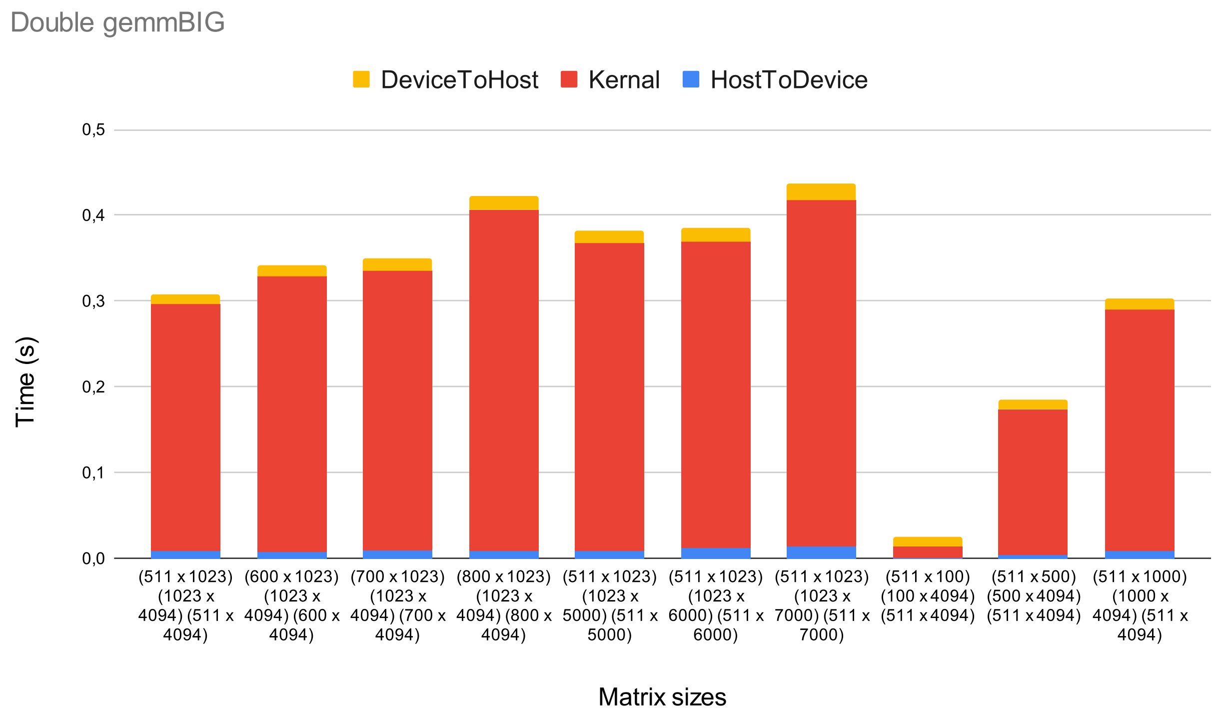
Kernal	gemmShared	gemmAtomicAdd	gemmBIG
Cuda threads	2140150782	2140150782	2092034
Achieved occupancy (%)	16.33	74.01	98.64

6. Further increase the size of matrix A and B, plot a stacked bar chart showing the breakdown of time including (1) data copy from host to device (2) the CUDA kernel (3) data copy from device to host. For this, you will need to add simple CPU timers to your code regions. Explain what you observe.

    ANSWER: In the plot one can see that the kernal time is by far the biggest contributing factor to the total time spent running the program. One can also see that the kernal called gemmBIG is the fastest. I assume this is becuase it has a order of magnitude less kernals (but each kernal does more work). This indicates that the overhead of creating kernals is substantial compared to the work done in gemmShared and gemmAtomicAdd.

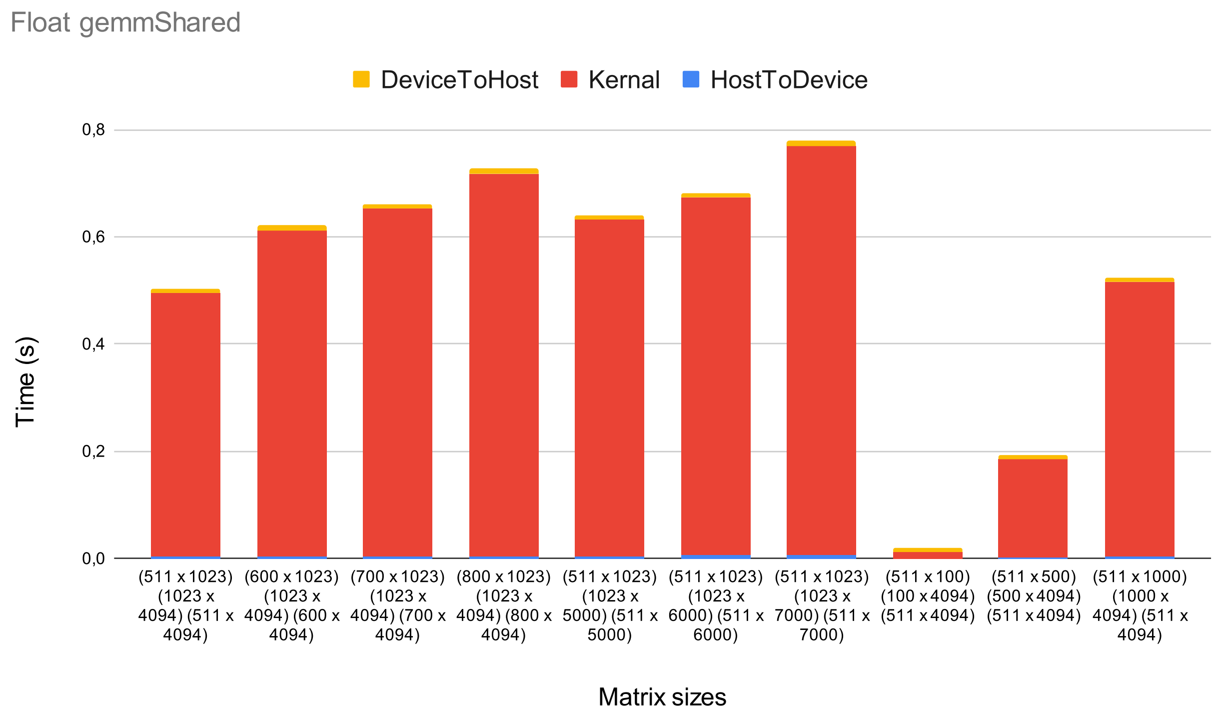

Double gemmShared
DeviceToHost
Kernal
HostToDevice
1,25
1,00
0,75
0,50
0,25
0,00
Time (s)
(511 x 1023) (1023 x 4094) (511 x 4094)
(600 x 1023) (1023 x 4094) (600 x 4094)
(700 x 1023) (1023 x 4094) (700 x 4094)
(800 x 1023) (1023 x 4094) (800 x 4094)
(511 x 1023) (1023 x 5000) (511 x 5000)
(511 x 1023) (1023 x 6000) (511 x 6000)
(511 x 1023) (1023 x 7000) (511 x 7000)
(511 x 100) (100 x 4094) (511 x 4094)
(511 x 500) (500 x 4094) (511 x 4094)
(511 x 1000) (1000 x 4094) (511 x 4094)
Matrix sizes

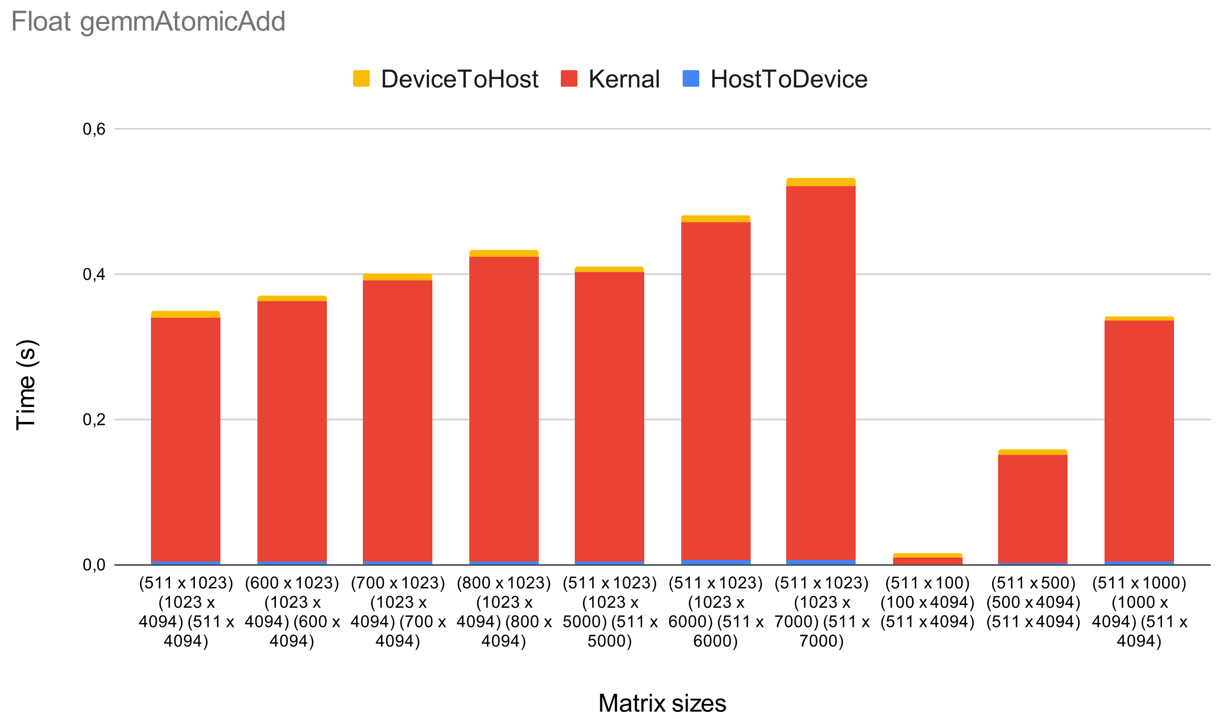

Double gemmAtomicAdd
DeviceToHost
Kernal
HostToDevice
0,6
0,4
0,2
0,0
Time (s)
(511 x 1023) (1023 x 4094) (511 x 4094)
(600 x 1023) (1023 x 4094) (600 x 4094)
(700 x 1023) (1023 x 4094) (700 x 4094)
(800 x 1023) (1023 x 4094) (800 x 4094)
(511 x 1023) (1023 x 5000) (511 x 5000)
(511 x 1023) (1023 x 6000) (511 x 6000)
(511 x 1023) (1023 x 7000) (511 x 7000)
(511 x 100) (100 x 4094) (511 x 4094)
(511 x 500) (500 x 4094) (511 x 4094)
(511 x 1000) (1000 x 4094) (511 x 4094)
Matrix sizes

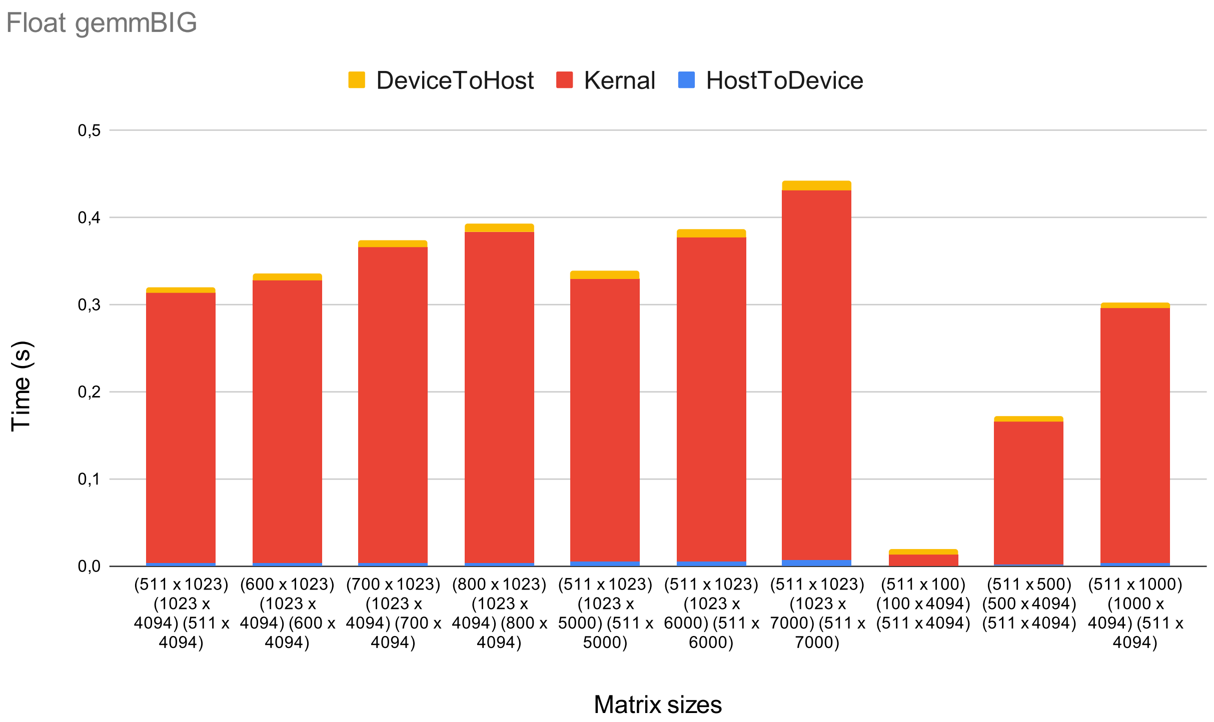


7. Now, change DataType from double to float, re-plot the a stacked bar chart showing the time breakdown. Explain what you observe.

   ANSWER: Firstly I had to decrese the max random number from 10000 to 100 and increse the tolerane from 0.004 to 1. This is because otherwise the float was not able to store the result to high enough precision.


Float gemmShared
DeviceToHost
Kernal
HostToDevice
Time (s)
0,0
0,2
0,4
0,6
0,8
(511 x 1023) (1023 x 4094) (511 x 4094)
(600 x 1023) (1023 x 4094) (600 x 4094)
(700 x 1023) (1023 x 4094) (700 x 4094)
(800 x 1023) (1023 x 4094) (800 x 4094)
(511 x 1023) (1023 x 5000) (511 x 5000)
(511 x 1023) (1023 x 6000) (511 x 6000)
(511 x 1023) (1023 x 7000) (511 x 7000)
(511 x 100) (100 x 4094) (511 x 4094)
(511 x 500) (500 x 4094) (511 x 4094)
(511 x 1000) (1000 x 4094) (511 x 4094)
Matrix sizes


Float gemmAtomicAdd
DeviceToHost
Kernal
HostToDevice
Time (s)
0,0
0,2
0,4
0,6
(511 x 1023) (1023 x 4094) (511 x 4094)
(600 x 1023) (1023 x 4094) (600 x 4094)
(700 x 1023) (1023 x 4094) (700 x 4094)
(800 x 1023) (1023 x 4094) (800 x 4094)
(511 x 1023) (1023 x 5000) (511 x 5000)
(511 x 1023) (1023 x 6000) (511 x 6000)
(511 x 1023) (1023 x 7000) (511 x 7000)
(511 x 100) (100 x 4094) (511 x 4094)
(511 x 500) (500 x 4094) (511 x 4094)
(511 x 1000) (1000 x 4094) (511 x 4094)
Matrix sizes


Float gemmBIG
DeviceToHost
Kernal
HostToDevice
Time (s)
0,5
0,4
0,3
0,2
0,1
0,0
(511 x 1023) (1023 x 4094) (511 x 4094)
(600 x 1023) (1023 x 4094) (600 x 4094)
(700 x 1023) (1023 x 4094) (700 x 4094)
(800 x 1023) (1023 x 4094) (800 x 4094)
(511 x 1023) (1023 x 5000) (511 x 5000)
(511 x 1023) (1023 x 6000) (511 x 6000)
(511 x 1023) (1023 x 7000) (511 x 7000)
(511 x 100) (100 x 4094) (511 x 4094)
(511 x 500) (500 x 4094) (511 x 4094)
(511 x 1000) (1000 x 4094) (511 x 4094)
Matrix sizes