GPU programming - assignment 2
Dr. Cherif Salama

Team members:

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GPU Model: GeForce RTX 3090

```
Fri Nov  4 19:33:12 2022
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 520.61.05    Driver Version: 520.61.05    CUDA Version: 11.8     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  NVIDIA GeForce ...  On   | 00000000:02:00.0  On |                  N/A |
|  0%   41C    P8    25W / 350W |    366MiB / 24576MiB |      6%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|    0   N/A  N/A       950      G   /usr/lib/xorg/Xorg                194MiB |
|    0   N/A  N/A      1459      G   /usr/bin/gnome-shell               38MiB |
|    0   N/A  N/A    224141      G   ...RendererForSitePerProcess      131MiB |
+-----------------------------------------------------------------------------+
```

```
cse-p07-g07f@csep07g07f:~/GPU_programming_with_CUDA$ nvidia-smi --query-gpu=name
 --format=csv,noheader
NVIDIA GeForce RTX 3090
```

GeForce and TITAN Products

GPU	Compute Capability
GeForce RTX 3090 Ti	8.6
GeForce RTX 3090	8.6

We are using the 8.6
For the full-table, check this link:
https://docs.nvidia.com/cuda/cuda-c-programming-guide/#features-and-technical-specifications

Note that the KB and K units used in the following table correspond to 1024 bytes (i.e., a KiB) and 1024 respectively.

Table 15. Technical Specifications per Compute Capability

	Compute Capability															
Technical Specifications	**3.5**	**3.7**	**5.0**	**5.2**	**5.3**	**6.0**	**6.1**	**6.2**	**7.0**	**7.2**	**7.5**	**8.0**	**8.6**	**8.7**	**8.9**	**9.0**
Maximum number of resident grids per device (Concurrent Kernel Execution)	32				16	128	32	16	128	16	128					
Maximum dimensionality of grid of thread blocks	3															
Maximum x-dimension of a grid of thread blocks	$2^{31}-1$															
Maximum y- or z-dimension of a grid of thread blocks	65535															
Maximum dimensionality of a thread block	3															
Maximum x- or y-dimension of a block	1024															
Maximum z-dimension of a block	64															
Maximum number of threads per block	1024															
Warp size	32															
Maximum number of resident blocks per SM	16		32								16	32	16		24	32
Maximum number of resident warps per SM	64										32	64	48			64
Maximum number of resident threads per SM	2048										1024	2048	1536			2048
Number of 32-bit registers per SM	64 K	128 K	64 K													
Maximum number of 32-bit registers per thread block	64 K				32 K	64 K		32 K	64 K							
Maximum number of 32-bit registers per thread	255															
Maximum amount of shared memory per SM	48 KB	112 KB	64 KB	96 KB	64 KB		96 KB	64 KB	96 KB		64 KB	164 KB	100 KB	164 KB	100 KB	228 KB
Maximum amount of shared memory per thread block [34]	48 KB								96 KB	96 KB	64 KB	163 KB	99 KB	163 KB	99 KB	227 KB
Number of shared memory banks	32															
Maximum amount of local memory per thread	512 KB															
Constant memory size	64 KB															
Cache working set per SM for constant memory	8 KB					4 KB	8 KB									
Cache working set per SM for texture memory	Between 12 KB and 48 KB					Between 24 KB and 48 KB			32 - 128 KB		32 or 64 KB	28KB - 192 KB	28KB - 128 KB	28KB - 192 KB	28KB - 128 KB	28KB - 256 KB
Maximum width for a 1D texture reference bound to a CUDA array	65536					131072										
Maximum width for a 1D texture reference bound to linear memory	2^{27}					2^{28}	2^{27}		2^{28}	2^{27}	2^{28}					
Maximum width and number of layers for a 1D layered texture reference	16384 x 2048					32768 x 2048										
Maximum width and height for a 2D texture reference bound to a CUDA array	65536 x 65536					131072 x 65536										

All the tests reported are for these matrices:

```
Dimensions of A:        1523x3232
Dimensions of B:        3232x1711
```

Notes:
The FLOPS calculation is a very complicated process, using counters is an option, but given the nature of the matrix-matrix multiplication problem, there is a theoritical proof for the number of calculations needed that neglects the simple loop variables.

1 Answer

Sorted by: Highest score (default)

4

There are $n \times m$ elements in the output matrix. Each of them is obtained by p multiplications (1 element from the first matrix and 1 from the second), then summing up. Since you have p products, you add $p - 1$ of them to the first one. So the number of operations for one element in the output matrix is p multiplications and $p - 1$ additions, meaning $2p - 1$ FLOPS. Then for all elements, you get $n \times m \times (2p - 1)$ FLOPS.

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answered Jan 17, 2020 at 22:51

Andrei

34.1k ● 5 ■ 24 ▲ 48

A more complete formulations of the FLOPS problem for the common matrices and vector problems is here:

vector-vector operations (x, $y \in \mathbf{R}^n$)

- inner product $x^T y$: $2n - 1$ flops (or $2n$ if n is large)
- sum $x + y$, scalar multiplication αx: n flops

matrix-vector product $y = Ax$ with $A \in \mathbf{R}^{m \times n}$

- $m(2n - 1)$ flops (or $2mn$ if n large)
- $2N$ if A is sparse with N nonzero elements
- $2p(n + m)$ if A is given as $A = UV^T$, $U \in \mathbf{R}^{m \times p}$, $V \in \mathbf{R}^{n \times p}$

matrix-matrix product $C = AB$ with $A \in \mathbf{R}^{m \times n}$, $B \in \mathbf{R}^{n \times p}$

- $mp(2n - 1)$ flops (or $2mnp$ if n large)
- less if A and/or B are sparse
- $(1/2)m(m + 1)(2n - 1) \approx m^2 n$ if $m = p$ and C symmetric

Task 1

We tested it with blocks of 16x16 threads, and 32x32
We also computed the GFLOPS for both the GPU and the CPU versions as well as the total time with and without the data transfer times.

Run 1:

Number of floating points operations needed for this matrix: **1.68416e+10**
CPU took: **38.4671 seconds**
Thus, CPU GFLOPS: 4.37819e+08

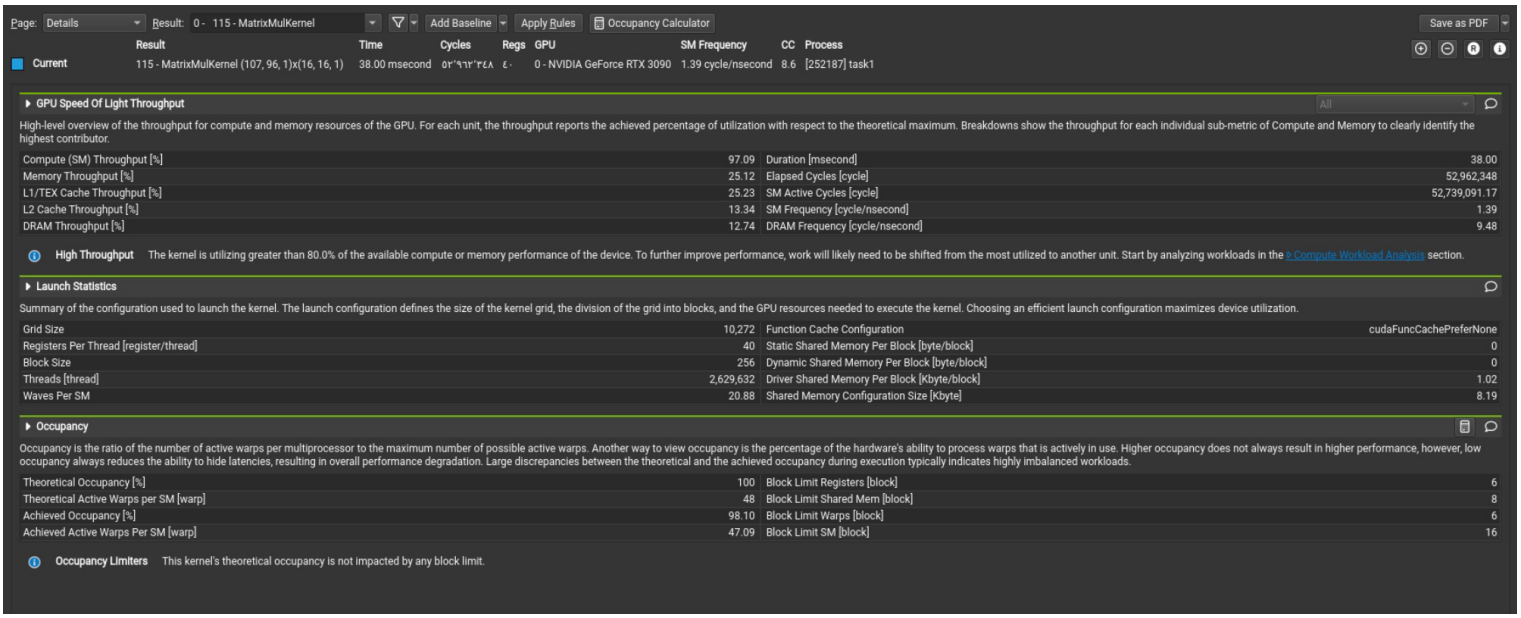
GPU with blockSize: **16x16**
Total number of blocks: **10272**
Total number of threads: **2629632**
GPU matrix multiplication took **209730080** nanoseconds (**WITHOUT DATA TRANSFER**)
GPU matrix multiplication took **347687000** nanoseconds (**WITH DATA TRANSFER**)
Therefore, data transfer takes about: (**347687000-209730080 / 347687000) = 0.39678 or 40% of the whole operation!**

GPU GFLOPS without data transfer: 4.84391e+11
This is (**1106.37** times the GFLOPS of CPU!)

GPU GFLOPS **with data transfer**: **8.03014e+10 (still 183.41 times the CPU)**

```
GPU ./gpu_assignment

Starting...
Dimensions of A: 1523x3232
Dimensions of B: 3232x1711
Starting CPU matrix multiplication...
CPU matrix multiplication took 38467801451 nanoseconds

FLOPS: : 1.68416e+10

Time in seconds: 38.4671

CPU GFLOPS: 4.37819e+08

Starting GPU matrix multiplication...
Total number of blocks: 10272
Total number of threads: 2629632

GPU matrix multiplication took 209730080 nanoseconds (WITHOUT DATA TRANSFER)
GPU matrix multiplication took 347687000 nanoseconds (WITH  DATA TRANSFER)

FLOPS: : 1.68416e+10

Time in seconds: 0.20973008

GPU GFLOPS of kernel only: 4.84391e+11

FLOPS: : 1.68416e+10

Time in seconds: 0.347687


GPU GFLOPS with copy: 8.03014e+10

Comparing matrices...

Matrices are equal
GPU
```

GPU Utilization profiling and occupancy analysis: (ZOOM IN for more readability)



You can see a few key notes from the NSight-compute analysis:
Our theoretical occupancy was: 100% so our kernel is not impacted by any block limites
The achieved occupancy was 98.10% which is really good.

Caching was utilized although our task implementation was pure brute-force, which made it a little faster, but still nothing compared to the second and third tasks.

Run 2: (32x32 blocks)

Number of floating points operations needed for this matrix: **1.68416e+10**
CPU took: **38.8542 seconds**
Thus, CPU GFLOPS: 4.33457e+08 (slightly less than last run, which is normal)

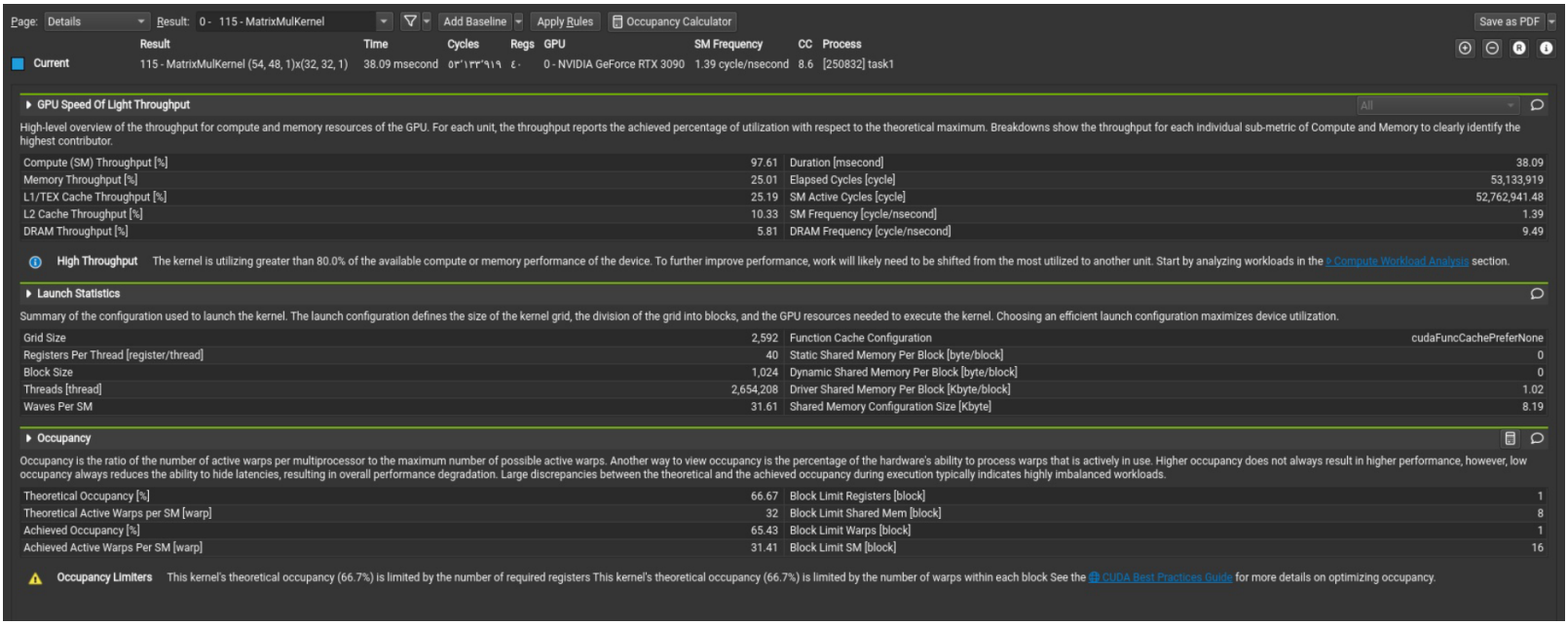
GPU with blockSize: **32x32**
Total number of blocks: **2592**
Total number of threads: **2654208**
GPU matrix multiplication took **126222238** nanoseconds (**WITHOUT DATA TRANSFER**)
GPU matrix multiplication took **314460000** nanoseconds (**WITH DATA TRANSFER**)
Therefore, data transfer takes about: (**314460000-126222238 / 314460000) = 0.5986 or 60% of the whole process**

GPU GFLOPS without data transfer: 5.35574e+11
This is (**1235.58** times the GFLOPS of CPU!)

GPU GFLOPS **with data transfer**: **1.33428e+11(**still **307.8** times the CPU**)**

Therefore:
The 32x32 blocks is faster than the 16x16 block size by 10.57%
5.35574e+11 / 4.84391e+11 = 1.10566463869

GPU Utilization profiling and occupancy analysis: (ZOOM IN for more readability)



You can see a few key notes from the NSight-compute analysis:
Our theoretical occupancy was: 66.67%, which is very low compared to the 16x16

The achieved occupancy was even lower at 65.43%.
It turns out that we are heavily impacted by the number of registers required per block.
So, we tried a better implementation that doesn't pass the dimensions of the A to function parametrs, but uses the global #defines instead to see the difference.

Yet, it remains faster because occupancy doesn't mean higher performance, but it might be more suitable for hiding latencies.

```
● → GPU ./gpu_assignment

  Starting...
  Dimensions of A: 1523x3232
  Dimensions of B: 3232x1711
  Starting CPU matrix multiplication...
  CPU matrix multiplication took 3.8541e+10 nanoseconds

  FLOPS: : 1.68416e+10

  Time in seconds:  38.8542

  CPU GFLOPS: 4.37819e+08

  Starting GPU matrix multiplication...
  Total number of blocks: 2592
  Total number of threads: 2654208

  GPU matrix multiplication took 126222238 nanoseconds (WITHOUT DATA TRANSFER)
  GPU matrix multiplication took 314460000 nanoseconds (WITH  DATA TRANSFER)

  FLOPS: : 1.68416e+10

  Time in seconds: 0.12622

  GPU GFLOPS of kernel only:  5.35574e+11

  FLOPS: : 1.68416e+10

  Time in seconds: 0.314460000

  GPU GFLOPS with copy: 1.33428e+11

  Comparing matrices...

  Matrices are equal
```

Task 2

RUN 1 (16x16 blocks):

This time, we implemented the matrix-matrix multiplication code using tiling and shared memory to see how much speedup would we get from reducing global memory accesses.

Dimensions of A: **1523x3232**
Dimensions of B: **3232x1711**

CPU matrix multiplication took 37857235971 nanoseconds (37.8572 seconds)

FLOPS: 1.68416e+10 (**from the equation**)

CPU GFLOPS: **4.44872e+08**

For GPU code with 16x16 blocks:

Total number of blocks: **10272**
Total number of threads: **2629632**

GPU matrix multiplication took **190998933** nanoseconds or **0.190999** seconds

FLOPS: **1.68416e+10**

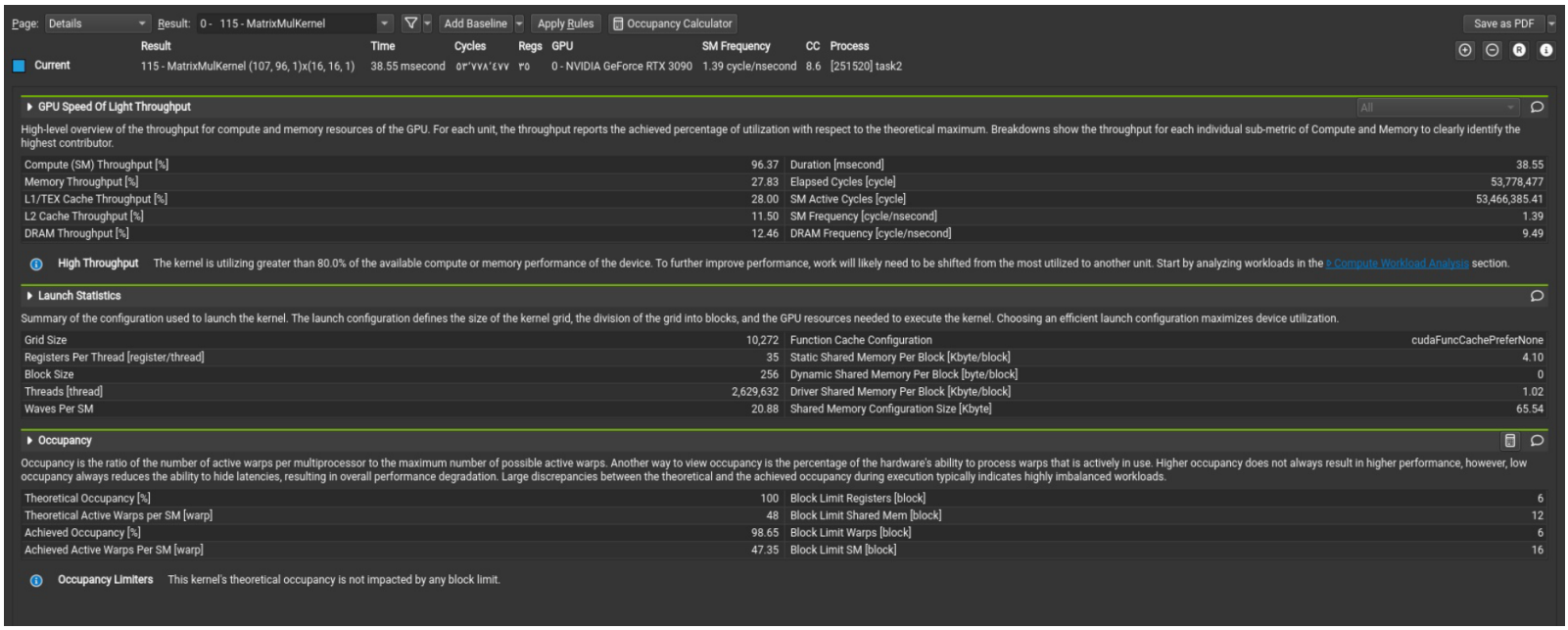
Time in seconds for the kernel alone without data transfer: **0.0687013**

GPU GFLOPS of kernel only without data transfer: **2.45143e+11**

GPU GFLOPS with copy: **8.81766e+10**

Speedup over CPU: 551 and 198 for kernel only and kernel with data transfer respectively

GPU utilization and occupancy analysis:



You can see we have a theoritical occupancy of 100% and achieved 98.65%

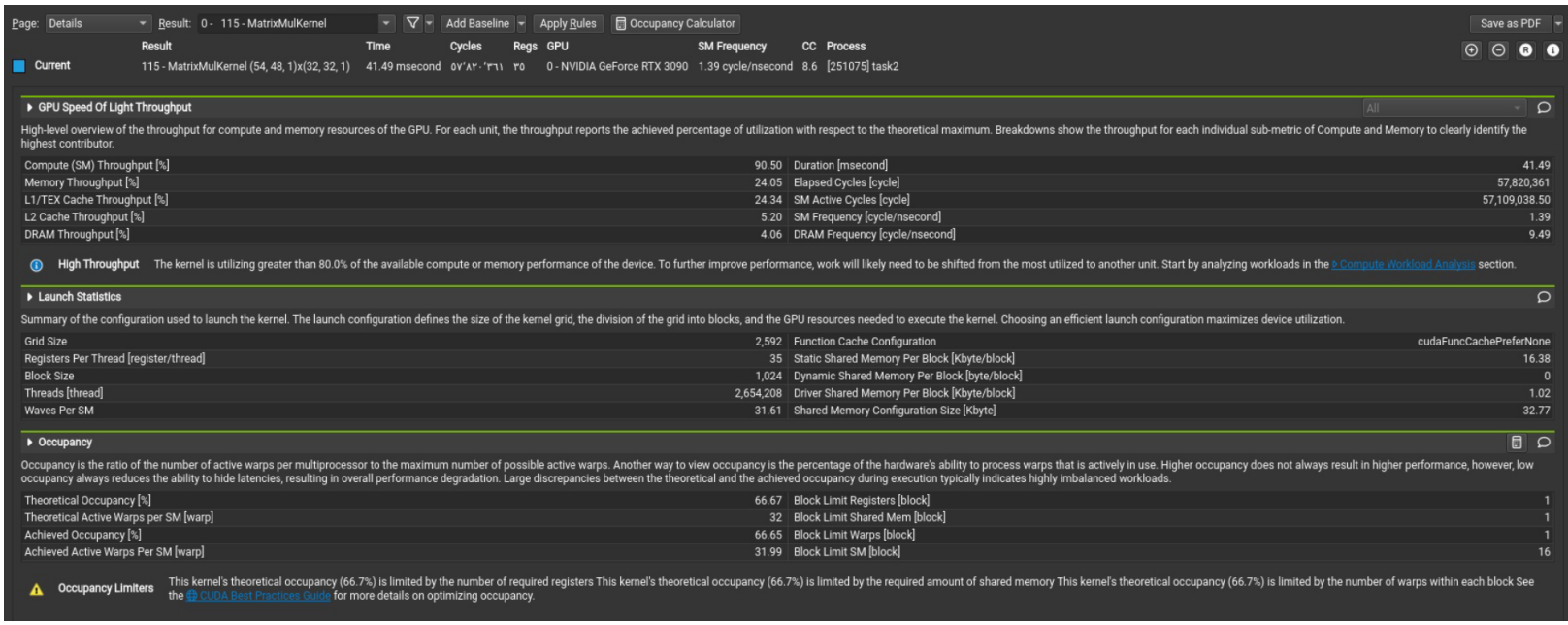
```
→  GPU ./gpu_assignment

  Starting...
  Dimensions of A: 1523x3232
  Dimensions of B: 3232x1711
  Starting CPU matrix multiplication...
  CPU matrix multiplication took 37857235971 nanoseconds

  FLOPS: : 1.68416e+10

  Time in seconds:  37.8572

  CPU GFLOPS: 4.44872e+08


  Starting GPU matrix multiplication...
  Total number of blocks: 10272
  Total number of threads: 2629632

  GPU matrix multiplication took 190998933 nanoseconds or  0.190999 seconds

  FLOPS: 1.68416e+10

  Time in seconds for the kernel alone without data transfer: 0.0687013

  GPU GFLOPS of kernel only without data transfer: 2.45143e+11

  FLOPS: 1.68416e+10
  GPU GFLOPS with copy: 8.81766e+10

  Comparing matrices...

  Matrices are equal
→  GPU
```

RUN 2 (32x32 blocks):
Dimensions of A: 1523x3232
Dimensions of B: 3232x1711
Starting CPU matrix multiplication...
CPU matrix multiplication took 39147475633 nanoseconds (39.1475 seconds)
FLOPS: 1.68416e+10 **CPU GFLOPS**: 4.3021e+08

For GPU (32x32)
Total number of blocks: 2592
Total number of threads: 2654208

GPU matrix multiplication took **134484166** nanoseconds
FLOPS: 1.68416e+10
Time in seconds: **0.0343415**
GPU GFLOPS of kernel only: **4.90416e+11**
Time in seconds with data transfer: **0.134484**
GPU GFLOPS with copy: **1.25231e+11**

Speedup over CPU: 1139.9 times without the transfer and 291 with the transfer
Speedup over the 16x16 is: 200% (2x)
Utilization analysis:



We now have theoretical occupancy of 66.67 and we are being limited by the size of the shared memory. This explains why the first version of the code might be a still competitive at this size. You can notice the throughput is down to 90.50% due to this overhead.

Task 3

Run 1:

Block size 16x16 and granularity is 2

Dimensions of A: 1523x3232
Dimensions of B: 3232x1711
CPU matrix multiplication took 37942277021 nanoseconds (**37.9423** seconds)

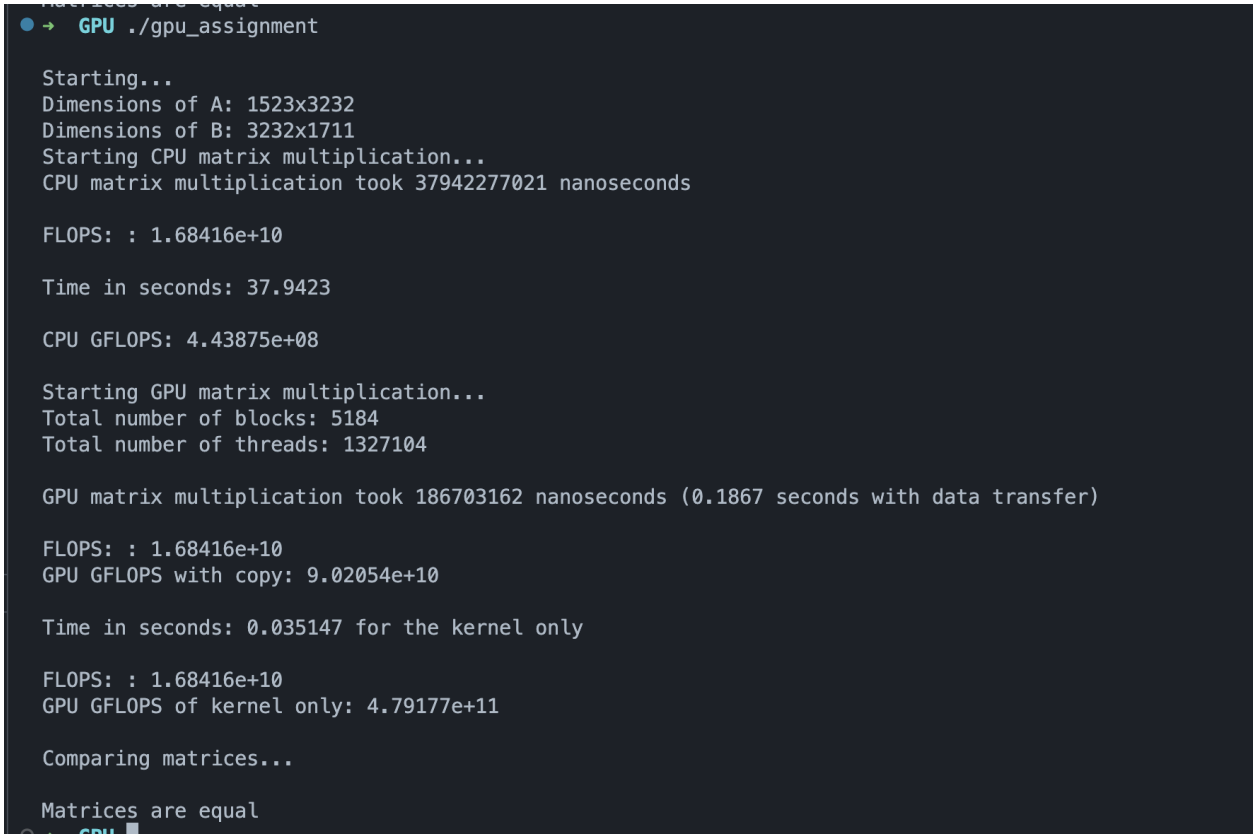
FLOPS: **1.68416e+10**
CPU GFLOPS: **4.43875e+08**

Total number of blocks: **5184**
Total number of threads: **1327104**

GPU matrix multiplication took 186703162 nanoseconds (0.1867 seconds with data transfer)
GPU GFLOPS with copy: 9.02054e+10

Time in seconds: **0.035147** for the kernel only
GPU GFLOPS of kernel only: **4.79177e+11**

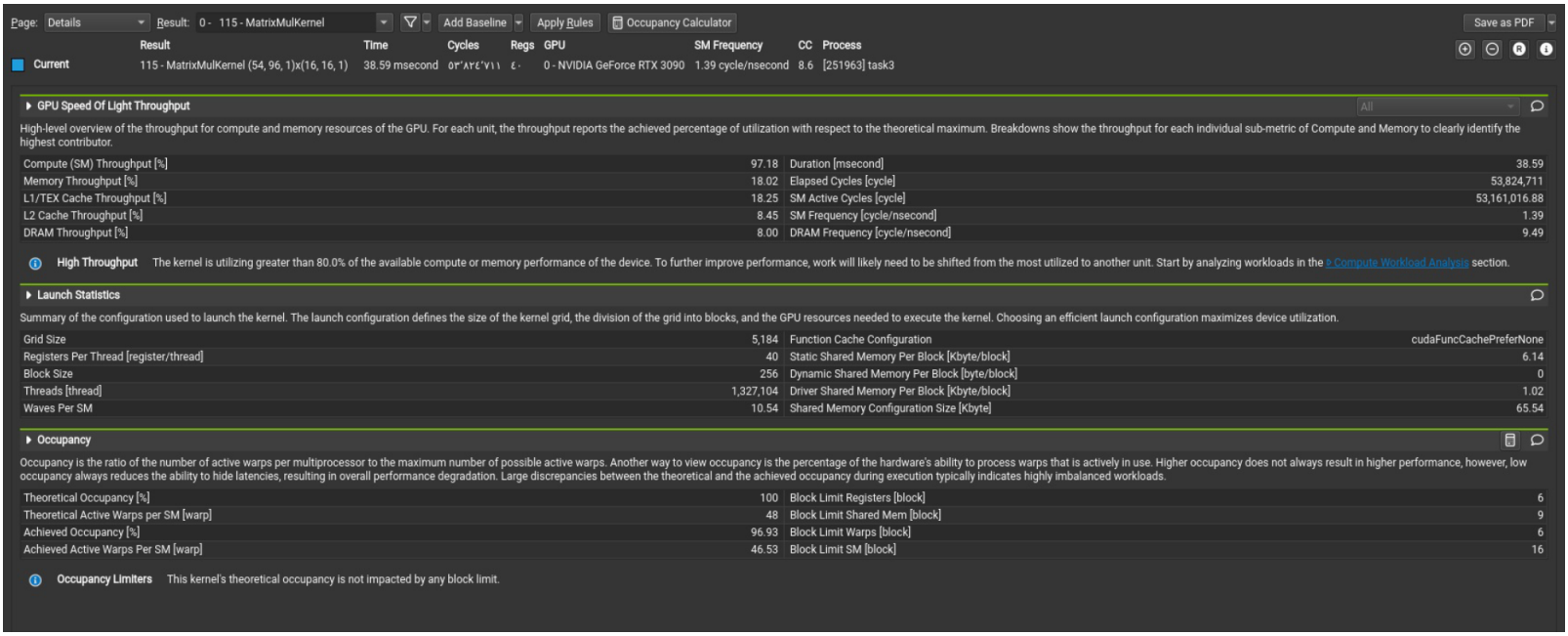
GPU speedups is: **1079.531 without data transfer over the CPU**


Matrices are equal
➜ GPU ./gpu_assignment
Starting...
Dimensions of A: 1523x3232
Dimensions of B: 3232x1711
Starting CPU matrix multiplication...
CPU matrix multiplication took 37942277021 nanoseconds
FLOPS: : 1.68416e+10
Time in seconds: 37.9423
CPU GFLOPS: 4.43875e+08
Starting GPU matrix multiplication...
Total number of blocks: 5184
Total number of threads: 1327104
GPU matrix multiplication took 186703162 nanoseconds (0.1867 seconds with data transfer)
FLOPS: : 1.68416e+10
GPU GFLOPS with copy: 9.02054e+10
Time in seconds: 0.035147 for the kernel only
FLOPS: : 1.68416e+10
GPU GFLOPS of kernel only: 4.79177e+11
Comparing matrices...
Matrices are equal

Utilization and occupancy analysis:

Another 100% theoretical occupancy and around 97% achieved.

You can also see it has very high compute SM throughput. **It is worth noting that it is still the slowest implemtation of all the tasks!**



Run 2:

Block size 16x16 and granularity is 4

Dimensions of A: 1523x3232
Dimensions of B: 3232x1711
CPU matrix multiplication took 37351129958 nanoseconds (37.3511 seconds)

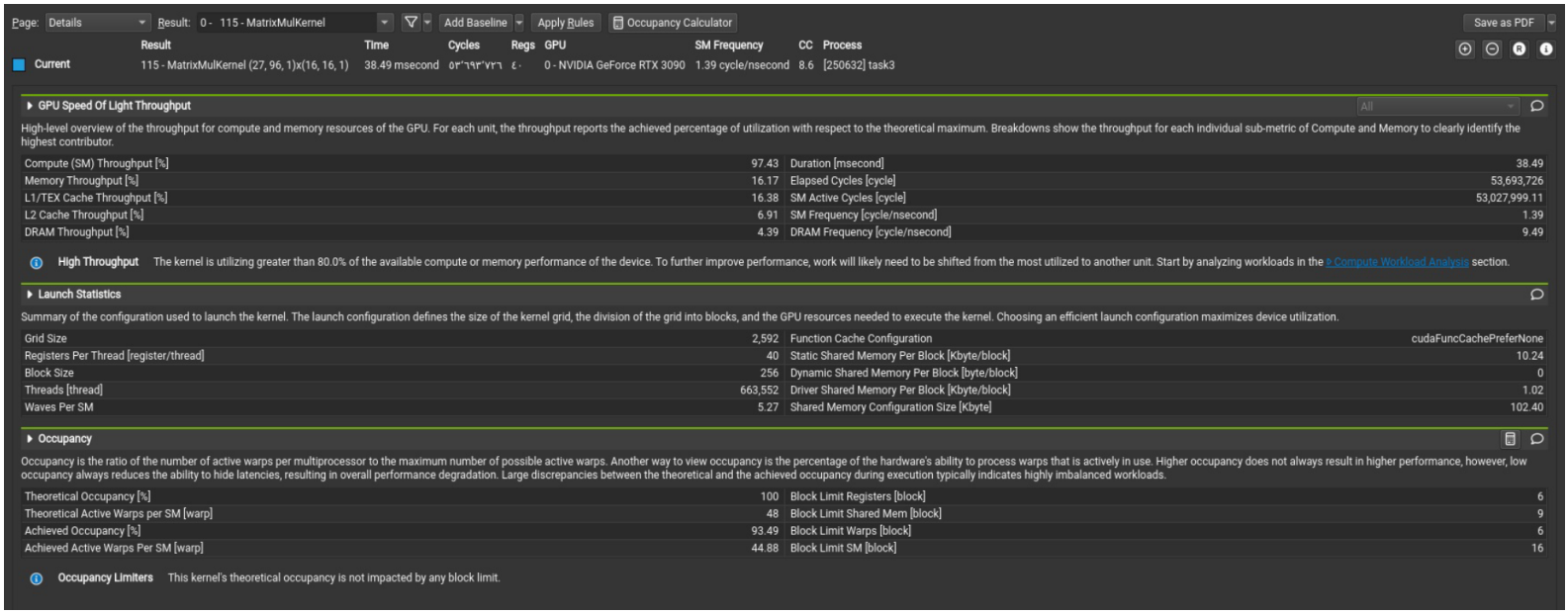
FLOPS: 1.68416e+10

Time in seconds: CPU GFLOPS: **4.509e+08**

GPU 16x16 blocks and granularity is 4
Total number of blocks: **2592**
Total number of threads: **663552**
GPU matrix multiplication took **158775880** nanoseconds (0.158776 seconds)

Time in seconds without data transfer: **0.031878**
GPU GFLOPS of kernel only**: 5.28315e+11 (FASTEST ONE SO FAR)**
GPU GFLOPS with copy: **1.06072e+11**

Speedup over CPU: 1190.23 without data transfer and 238.96 with data transfer
Utilization and occupancy analysis:
100% theoretical occupancy and 97.43% compute throughput and 16.17% memory throughput



```
● → GPU ./gpu_assignment

  Starting...
  Dimensions of A: 1523x3232
  Dimensions of B: 3232x1711
  Starting CPU matrix multiplication...
  CPU matrix multiplication took 37351129958 nanoseconds

  FLOPS: : 1.68416e+10

  Time in seconds: 37.3511

  CPU GFLOPS: 4.509e+08

  Starting GPU matrix multiplication...
  Total number of blocks: 2592
  Total number of threads: 663552

  GPU matrix multiplication took 158775880 nanoseconds (0.158776 seconds with data transfer)

  FLOPS: : 1.68416e+10
  GPU GFLOPS with copy: 1.06072e+11

  Time in seconds: 0.031878 for the kernel only

  FLOPS: : 1.68416e+10
  GPU GFLOPS of kernel only:  5.28315e+11

  Comparing matrices...

  Matrices are equal
```

Run 3:

Block size 32x32 and granularity is 2

Dimensions of A: 1523x3232
Dimensions of B: 3232x1711
CPU matrix multiplication took 38415860821 nanoseconds (38.4159 seconds)

FLOPS: 1.68416e+10

CPU GFLOPS: **4.38403e+08**

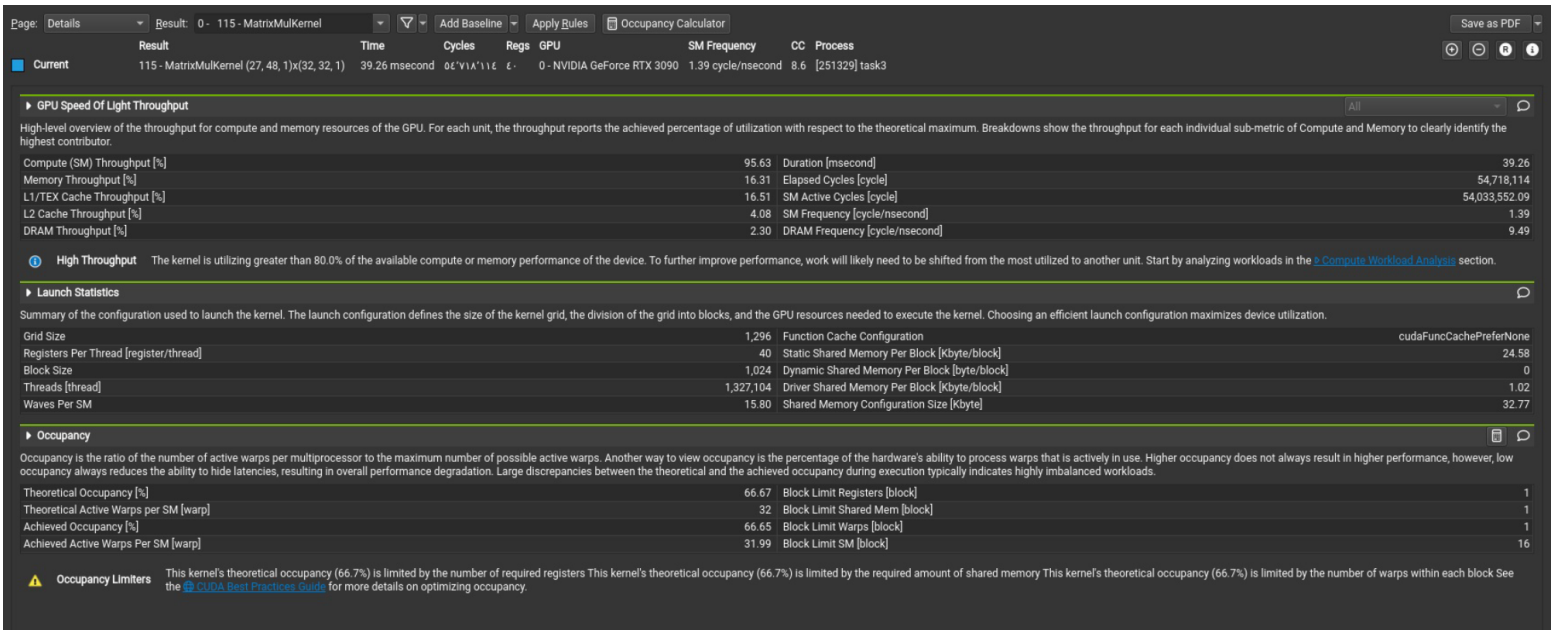
Total number of blocks: 1296
Total number of threads: 1327104
GPU matrix multiplication took 144913071 nanoseconds (0.144913 seconds)

Time in seconds without data transfer: **0.0359325**
GPU GFLOPS of kernel only: **4.68702e+11 (much slower than 16x16, profiler will show why)**

GPU GFLOPS with copy: **1.16219e+11**

Speedup over CPU: **1055.93** and **261.82** with and without data transfer

Utilization and occupancy analysis:
Our kernel has 66.67% occupancy and is being limited by the number of registers this time. Otherwise, everything is looking good with high SM throughput and same as usual memory throughput.




```
GPU ./gpu_assignment

Starting...
Dimensions of A: 1523x3232
Dimensions of B: 3232x1711
Starting CPU matrix multiplication...
CPU matrix multiplication took 38415860821 nanoseconds

FLOPS: : 1.68416e+10

Time in seconds: 38.4159

CPU GFLOPS: 4.38403e+08


Starting GPU matrix multiplication...
Total number of blocks: 1296
Total number of threads: 1327104

GPU matrix multiplication took 144913071 nanoseconds (0.144913 seconds with data transfer)

FLOPS: : 1.68416e+10
GPU GFLOPS with copy: 1.16219e+11

Time in seconds: 0.0359325 for the kernel only

FLOPS: : 1.68416e+10
GPU GFLOPS of kernel only:  4.68702e+11

Comparing matrices...

Matrices are equal
```

Run 4:

Block size 32x32 and granularity is 4

Dimensions of A: 1523x3232

Dimensions of B: 3232x1711

CPU matrix multiplication took 39488929569 nanoseconds (39.4889 seconds)

FLOPS: 1.68416e+10

CPU GFLOPS: **4.2649e+08**

Starting GPU matrix multiplication...

Total number of blocks: 672

Total number of threads: 688128

GPU matrix multiplication took 171116502 nanoseconds (0.171116 seconds)

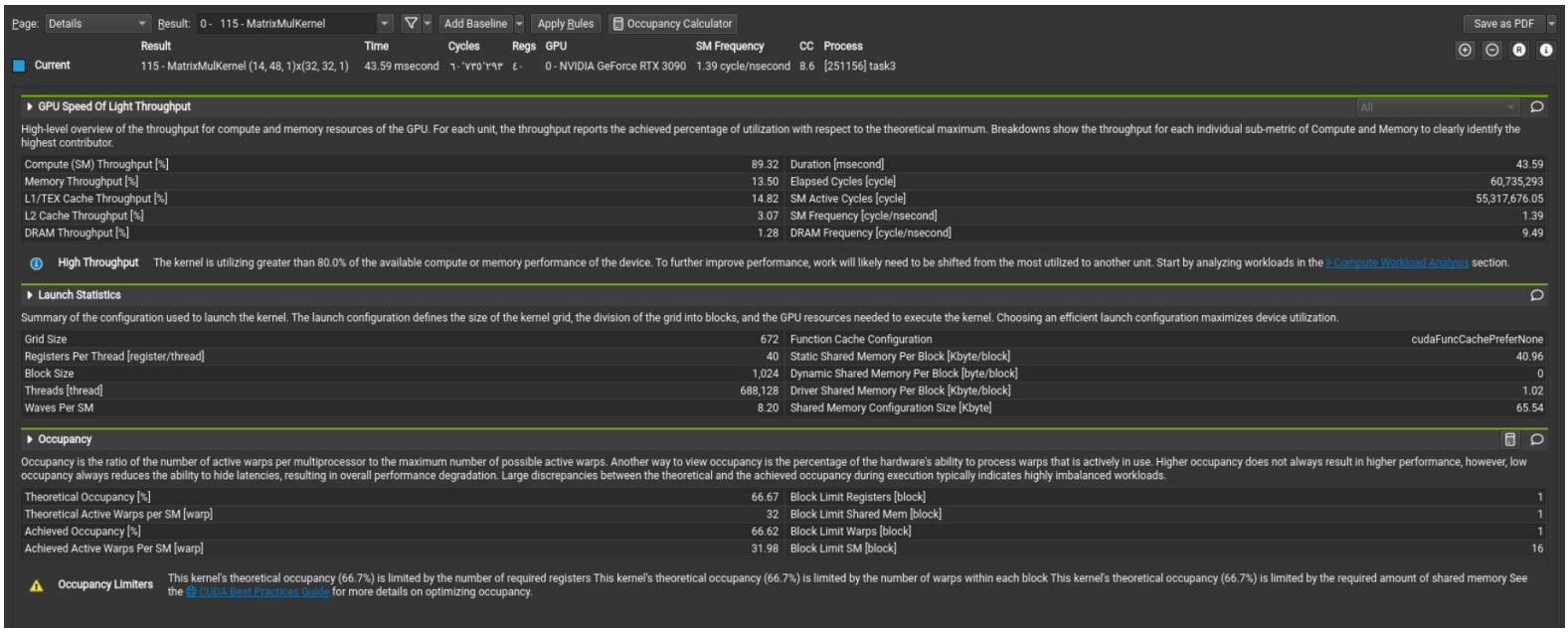
Time in seconds of kernel only: **0.0359663**

GPU GFLOPS of kernel only: **4.68262e+11**

GPU GFLOPS with copy: **9.8422e+10**

Speedup of GPU over CPU is: **1054.94** and **221.73**

Utilization and occupancy analysis:



Occupancy is limited due to the number of registers again and we have a 89.32 compute SM throughput.

More tests:

Problem: We noticed that sometimes, task 1, the simplest version without any shared memory or granularity, can outperform the more optimized versions, despite making sure both are implemented 100% correctly.

So, to verify this, we need to put both versions under bigger stress and larger tests so that the small differences would be magnified and see if the optimizations actually make it better or not.

So, we tested both with these matrices:

Matrix A: **2532** x **3232**

Matrix B: **3232** x **4711**

Task 1: 16x16 block size

CPU matrix multiplication took 193581901451 nanoseconds (193.582 seconds)

FLOPS: **7.68183e+10**

CPU GFLOPS: **3.96826e+08**

Total number of blocks: 46610
Total number of threads: 11932160
GPU matrix multiplication took 299241542 ns (0.299s with copy and allocation)

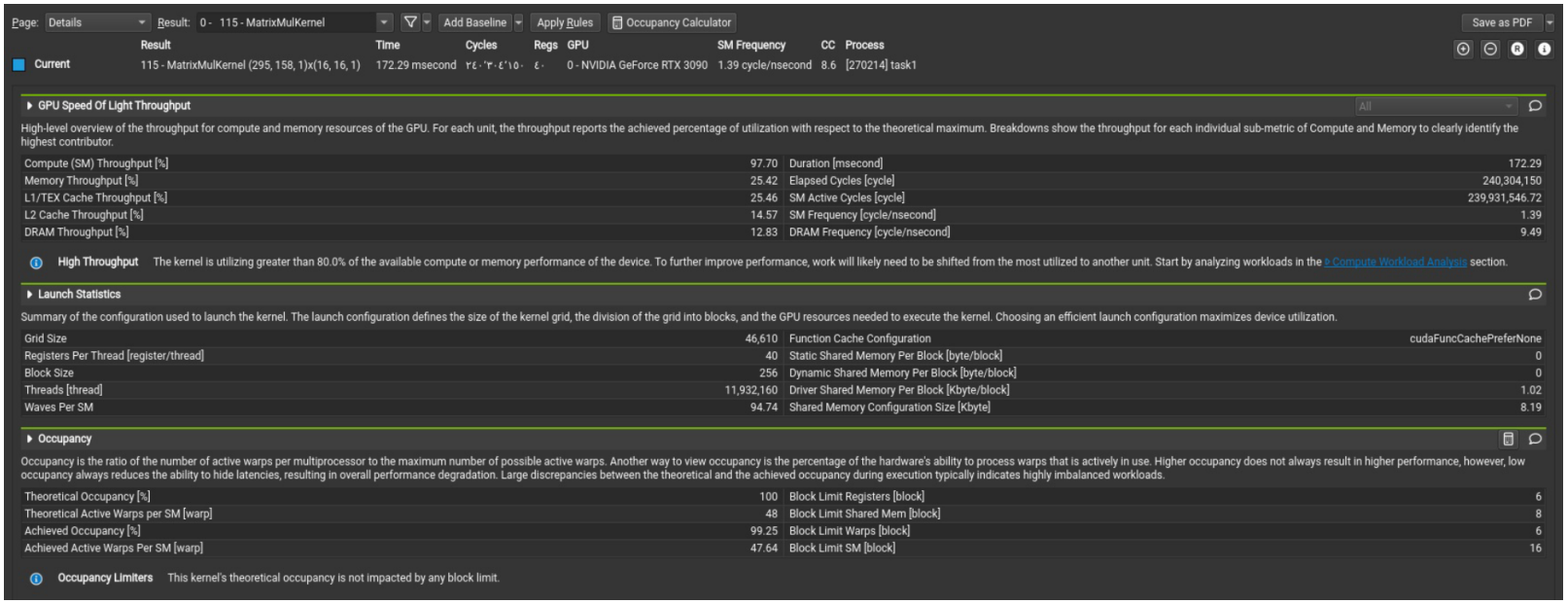
Time in seconds: 0.150121 for kernel only

GPU GFLOPS of kernel only: 5.11711e+11
GPU GFLOPS with copy: 2.5671e+11

Speedups over CPU: **1289.509 without data transfer**
And 646.90 with data transfer **(This makes it the fastest one test so far)**

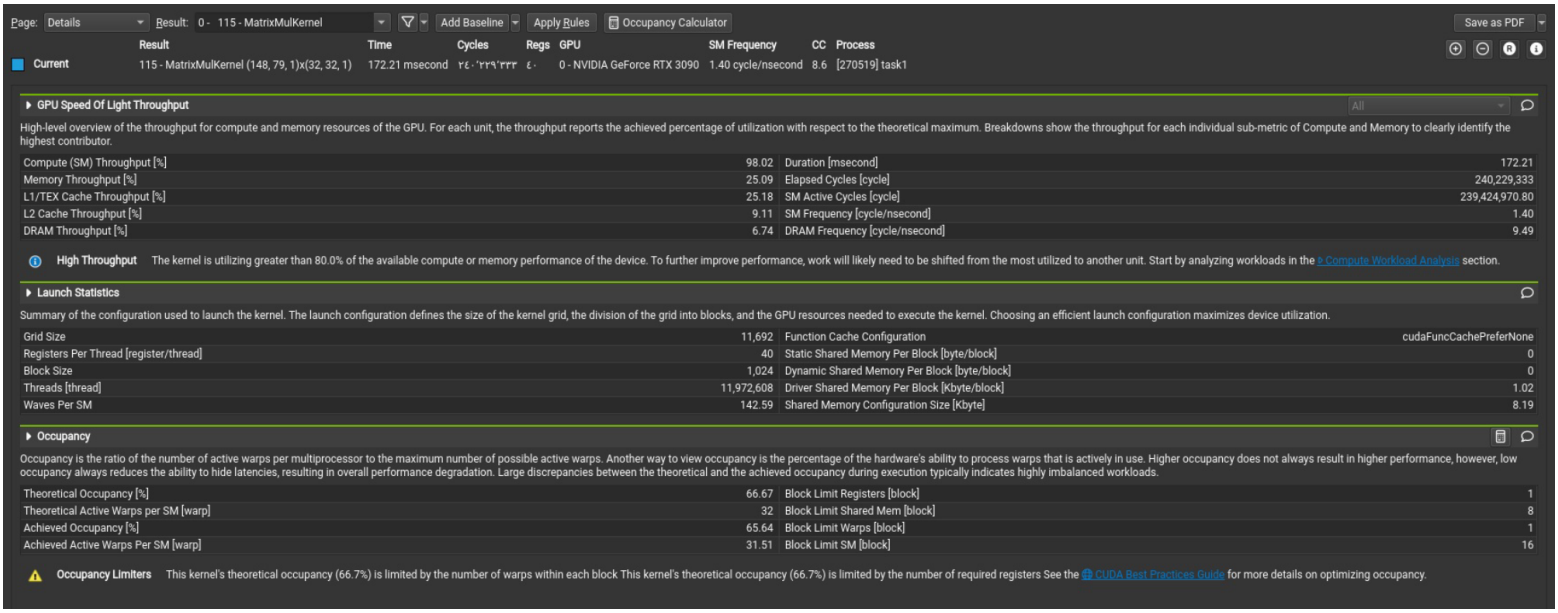
```
➜  GPU ./gpu_assignment
Starting...
Dimensions of A: 2523x3232
Dimensions of B: 3232x4711

Starting CPU matrix multiplication...
CPU matrix multiplication took 193581901451 nanoseconds

FLOPS: 7.68183e+10

Time in seconds: 193.582

CPU GFLOPS: 3.96826e+08

Starting GPU matrix multiplication...
Total number of blocks: 46610
Total number of threads: 11932160
GPU matrix multiplication took 299241542 nanoseconds

FLOPS: 7.68183e+10

Time in seconds: 0.150121

GPU GFLOPS of kernel only: 5.11711e+11

FLOPS: 7.68183e+10

Time in seconds: 0.299242

GPU GFLOPS with copy: 2.5671e+11
Comparing matrices...

Matrices are equal
```

Utilization and occupancy analysis:



Full-occupancy and very high memory throughput and compute throughput

We then tested it with bigger blocks **32x32**



And the occupancy dropped by more than 33% as the register file was not enough for this many threads in a block.

You can see in the screenshots from the Nsight compute that despite a 33% drop in occupancy, the timing is still lower than the 16x16 by a 0.1 second.

Task 2 for same matrices with 16x16 blocks

CPU matrix multiplication took 199626592983 nanoseconds (199.627 seconds)

FLOPS: 7.68183e+10
CPU GFLOPS: 3.8481e+08

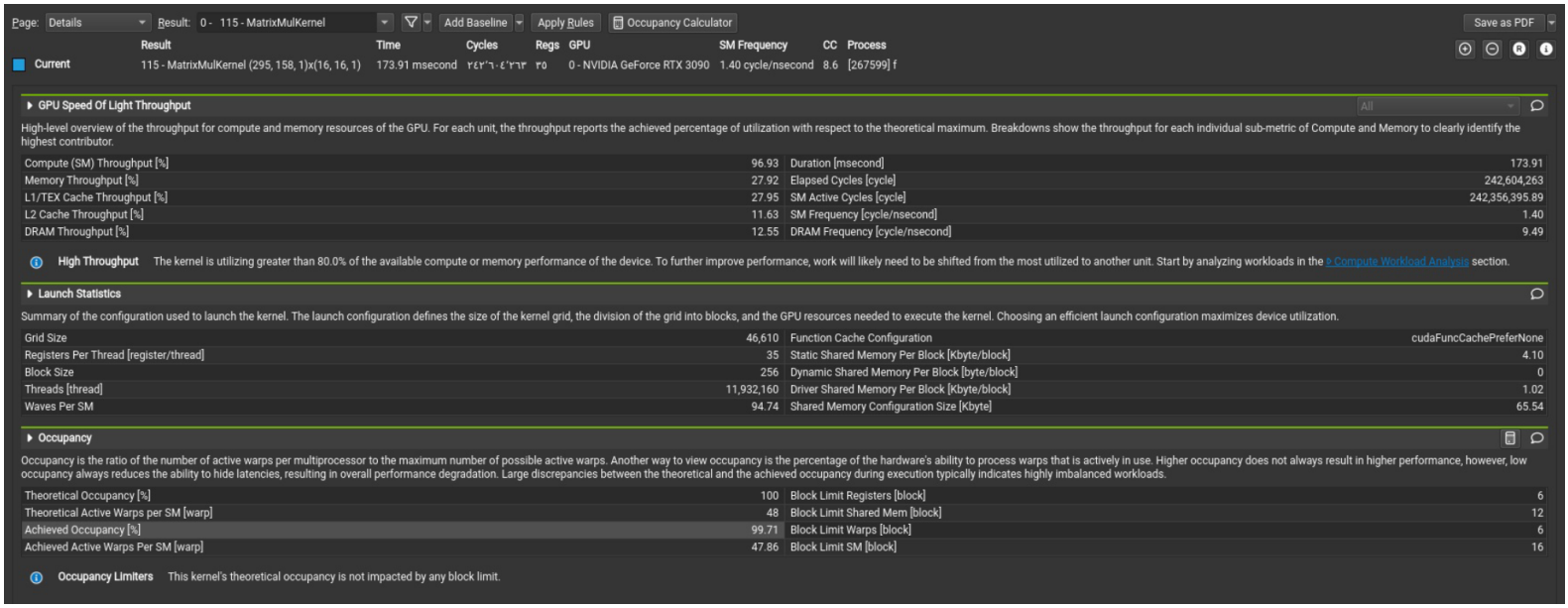
Total number of blocks: 46610
Total number of threads: 11932160

GPU matrix multiplication took 282432486 nanoseconds (0.2824 sec with copy and allocation)

Kernel only Time in seconds: 0.143208

GPU GFLOPS of kernel only: **5.36411e+11**
GPU GFLOPS with copy: **2.71988e+11**

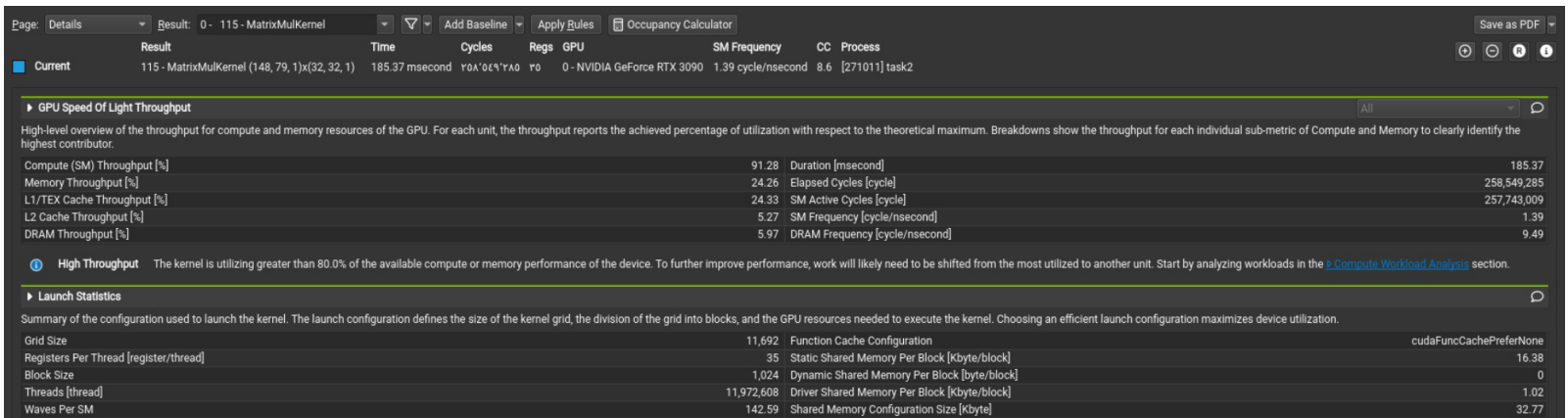
Speedup of Kernel over CPU is: (**1393.96** The fastest one we had)
Speedup of kernel + allocation and copy is **706.81 over the CPU (fastest overall)**



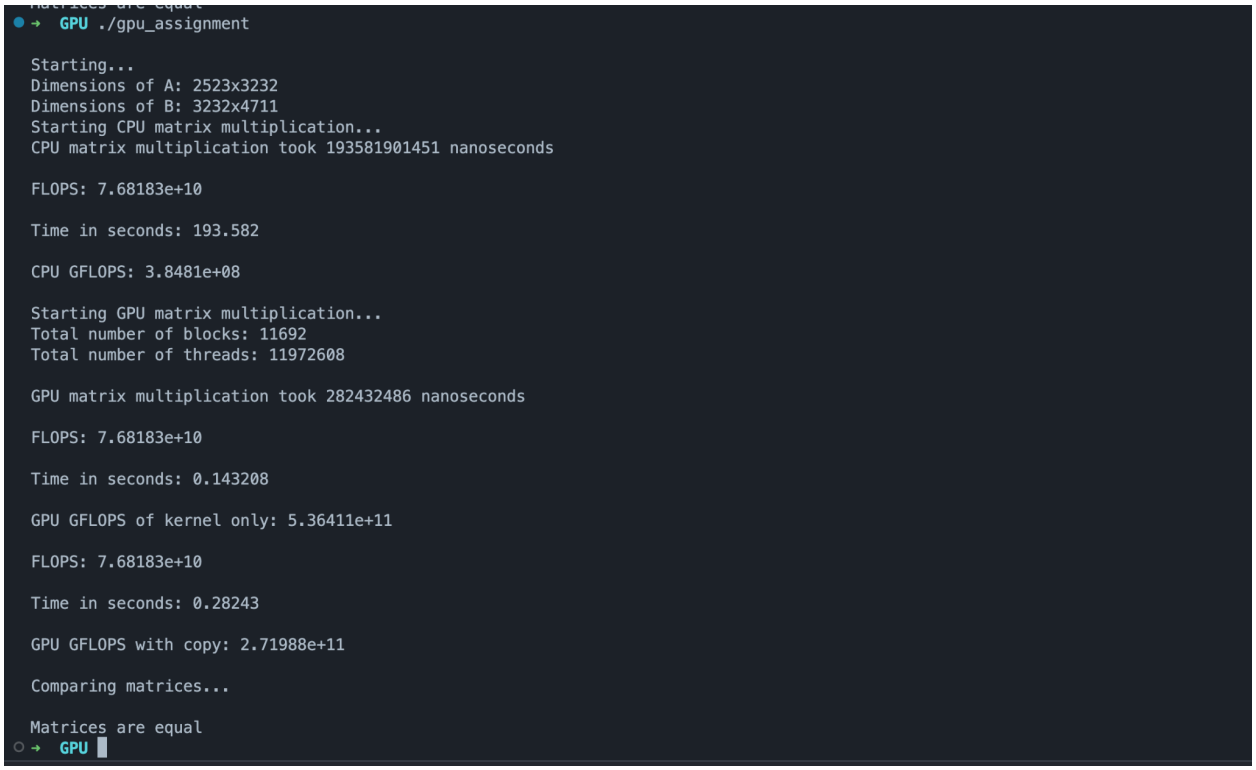
```
GPU ./gpu_assignment

Starting...
Dimensions of A: 2523x3232
Dimensions of B: 3232x4711
Starting CPU matrix multiplication...
CPU matrix multiplication took 199626592983 nanoseconds

FLOPS: 7.68183e+10

Time in seconds: 199.627

CPU GFLOPS: 3.8481e+08

Starting GPU matrix multiplication...
Total number of blocks: 46610
Total number of threads: 11932160

GPU matrix multiplication took 282432486 nanoseconds

FLOPS: 7.68183e+10

Time in seconds: 0.143208

GPU GFLOPS of kernel only: 5.36411e+11

FLOPS: 7.68183e+10

Time in seconds: 0.282432

GPU GFLOPS with copy: 2.71988e+11

Comparing matrices...

Matrices are equal
```

You can see that this has the highest achieved occupancy of all kernels tested. It also has one of the highest memory thorughputs of 28% and Compute throughput of 97%

We gave it another try at 32x32 blocks



Which limited occpuancy to 66.67 as shared memory was the limiting factor here unlike the previous test. This also resulted in around 91% Compute throughput which is significantly lower than previous implementations.



In the end, it was slower by 10 milliseconds as you can see in the Kernel duration in the upper right corner of the screenshot.

Additional notes:

We wrote the input and output matrices to files instead of dumping them to the terminal for easier testing and debugging. So taking screenshots was not that useful as you can never see both inputs and outputs as well as the CPU and GPU results in one screenshot.