CSE 625 Parallel Programming
Project 2
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Machine Specifications

The project was all performed on my home computer with the following specifications:

- **CPU**
  Intel(R) Core(TM) i9-10900K CPU @ 3.70GHz
  AVX2 (256-bit MM registers)
  10 cores / 20 threads
  20 MB Intel Smart Cache (L3-cache)

- **RAM**
  32 GB DDR4 RAM

- **GPU**
  TUF RTX3080 (Ampere GPU)
  8704 CUDA cores
  5 MB of L2-Cache
  10GB GDDR6X

Problem 1

1.) Row Major Memory stores each row of the matrix in sequential order with the last element of the first row being adjacent in memory to the first element in the seconds row and so on. Thus, the result is a 1-D array storing the information of the 2D matrix.

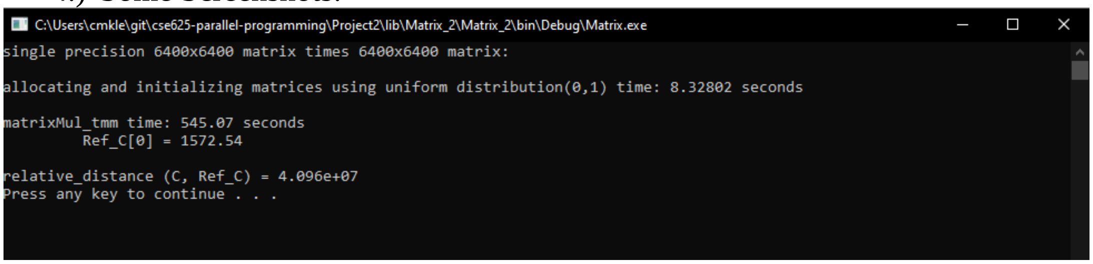
2.) Tmm speeds up the performance be performing a transpose on the matrix before attempting to multiply them. This is due to the fact that the locality is better than non-transposed matrices and so there are fewer cache misses on lookup. Avx_tmm improves upon this idea further by using __mm256 registers to perform SIMD operations.

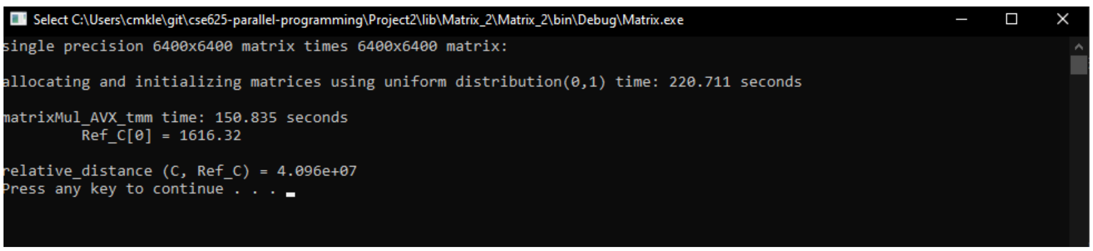
3.) Timing Table Results:

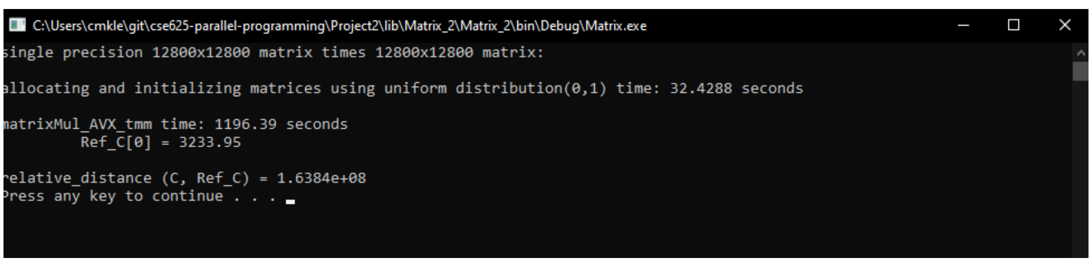
Problem 1.2	200	400	800	1,600	3,200	6,400	12,800
`matrixMul_RowMajor`	0.0158936	0.136338	1.16626	17.4047	165.364		
`matrixMul_tmm`	0.0153014	0.120813	0.964209	7.7588	63.4531	545.07	
`Speed-up`	3.87%	12.85%	21%	124%	161%		
`matrixMul_AVX_tmm`	0.004846	0.0344672	0.261497	2.20101	19.0317	150.835	1196.39

Speed-up	227.97%	396%	446%	791%	869%		

4.) Some Screenshots:







Problem 2

2.1

For loop timing table results:

	200X200	400X400	800X800
For-loop Timing	5.39s	41.6s	5m 31s

2.2

Numpy timing table results:

	200X200	400X400	800X800	1600X1600	3200X3200	6400X6400	12,800X12,800
`matmul` Timing	3.97ms	.991ms	3.47ms	16.4ms	136ms	1.24secs	10.8secs

Method to create the matrices

```
import numpy as np

def createMatrices(s):
    mat1 = np.random.random((s, s)).astype(np.float32)
    mat2 = np.random.random((s, s)).astype(np.float32)
    return (mat1, mat2)
```

For-loop multiplication implementation

```
import numpy as np
sizes = [200, 400, 800]

def multiplyMatrices(m1, m2, size):
    result = np.empty((size, size), dtype=float)
    for i in range(len(m1)):
        # iterate through columns of M2
        for j in range(len(m2[0])):
            # iterate through rows of M2
            for k in range(len(m2)):
                result[i][j] += m1[i][k] * m2[k][j]

def runTimingTests():
    for size in sizes:
        print("Multplying matrices of size", size)
        mat1, mat2 = createMatrices(size)
        %time multiplyMatrices(mat1, mat2, size)
        print("Done")

runTimingTests()
```

NumPy multiplication implementation

```
sizes = [200, 400, 800, 1600, 3200, 6400, 12800]

def runNumpyTimingTests():
    for size in sizes:
        print("Multplying matrices of size", size)
        mat1, mat2 = createMatrices(size)
        %time np.matmul(mat1, mat2)
        print("Done")
```

```
runNumpyTimingTests()
```

Screenshots:

```
Multplying matrices of size 200
Wall time: 5.39 s
Done
Multplying matrices of size 400
Wall time: 41.6 s
Done
Multplying matrices of size 800
Wall time: 5min 31s
Done
```

```
Multplying matrices of size 200
Wall time: 3.97 ms
Done
Multplying matrices of size 400
Wall time: 991 µs
Done
Multplying matrices of size 800
Wall time: 3.47 ms
Done
Multplying matrices of size 1600
Wall time: 16.4 ms
Done
Multplying matrices of size 3200
Wall time: 136 ms
Done
Multplying matrices of size 6400
Wall time: 1.24 s
Done
Multplying matrices of size 12800
Wall time: 10.8 s
Done
```

Problem 3

Each function was tested on float vectors of the indicated size with all elements equal to 1. This made the calculation easy to determine and check if correct.

Sequential Dot-Function:

```
float SequentialDot(const std::vector<float> &v1, const std::vector<float>
&v2)
{
    float result = 0;
    size_t length = (v1.size() <= v2.size() ? v1.size() : v2.size());
    for (int i = 0; i < length; ++i)
    {
        result += v1[i] * v2[i];
    }
    return result;
}
```

AVX Dot-function:

```
float AVXDot(const std::vector<float> &v1, const std::vector<float> &v2)
{
    __m256 C = _mm256_setzero_ps();
    size_t length = (v1.size() <= v2.size() ? v1.size() : v2.size());
    float result;

    for (int i = 0; i < length; i += 8)
    {
        __m256 X = _mm256_setzero_ps();
        const __m256 mmA = _mm256_loadu_ps((float *)&v1[i]);
        const __m256 mmB = _mm256_loadu_ps((float *)&v2[i]);
        X = _mm256_mul_ps(mmA, mmB);
        result += hsum256_ps_avx(X);
    }
    return result;
}
```

Test results in the following table:

	6,400,000	64,000,000
Sequential time	0.0206596 seconds	0.063169
AVX time	0.0144532 seconds	0.146274
Sequential result	6.4e+06	1.67772e+07
AVX result	6.4e+06	6.4e+07

The sequential dot result is not accurate for two vectors of size larger than 16,777,216. This is because 32-bit floats (according to IEEE-754) are stored in the following format:

sign (1 bit) + exponent (8 bits) + mantissa (23 bits). The mantissa is where the value is stored and 16,777,216 is exactly 2^24 so any number more precice (like 16,777,217) cannot be stored in a 32-bit float. This obviously causes a calculation issue and is the reason any number higher results in the same answer of 16,777,216 because it cannot increment. The simplest solution to this problem is to use a double instead to increase the precision, though this may slow performance.

AVX is accurate as it uses 256-bit registers to store 8 elements of the overall vector at a time, each in a 32-bit slot. Since each slot is occupied by only a single number, there is not issues with precision that causes it to fail.

Some Screenshots:

```
SeqDot time: 0.0206596 seconds
         Seq Dot Result = 6.4e+06

AVXDot time: 0.0144532 seconds
         AVX Dot Result = 6.4e+06

Press any key to continue . . .
```

```
SeqDot time: 0.207591 seconds
         Seq Dot Result = 1.67772e+07

AVXDot time: 0.146274 seconds
         AVX Dot Result = 6.4e+07
```

Problem 4

(25 points)

C++ Multi-threaded Matrix multiplication implementation

```
void matrixMul_RowMajor_threaded(float *C, float *A, float *B, int RA, int CA, int CB, int num_threads)
{
    // use lambda function
    auto multMatBlock = [&](const int& id, float *C, float *A, float *B, int RA, int CA, int CB)
    {
        // compute chunk size, lower and upper for task id
        const int chunk = (RA + num_threads-1) / num_threads;
        const int lower = id * chunk;
        const int upper = std::min(lower+chunk, RA);

        int row, col;
```

```
        for (row = lower; row < upper; row++)
        {
            for (col = 0; col < CB; ++col)
            {
                float Cvalue = 0;
                for (int k = 0; k < CA; k++)
                    Cvalue += A[row * CA + k] * B[k * CB + col];
                C[row * CB + col] = Cvalue;
            }
        }
    };

    std::vector<std::thread> threads;
    for (int id = 0; id < num_threads; id++)
    {
        std::cout<< "Creating thread Id: " << id << std::endl;
        threads.emplace_back(multMatBlock, id, C, A, B, RA, CA, CB);
    }

    for (auto& thread : threads)
    {
        thread.join();
    }

    std::cout<< "Threaded Matrix Multiplicaiton Complete" << std::endl;
}
```

Timing Table Results:

Timing Table	4 threads	8 threads	16 threads	20 threads	32 threads
3200x3200	39.9271	22.2554	16.723	14.8734	16.0783
6400x6400	405,894	261.577	392.952	196.498	210.766

Based on the timing results and system architecture, 20 threads seems to be optimal. For some reason, 16 threads was slower with the larger data set, but in both cases 20 was the highest performing. Since my machine has 20 threads to work with, 20 threads makes since to be the most optimal.