High Performance Computing (DD2356)

Assignment 1

Carried out by:

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EXERCISE-1:

Questions:

1. What is the performance in total execution time - do not consider data movement - according to our performance model on Beskow or your local computer for different sparse matrices nrows = 10², 10⁴, 10⁶ and 10⁸? **Hint:** Use **Time** = nnz*2c and calculate c from the given clock speed of the processor in use.

```
value of c for nrows =10^2 is nnz=460 and T =0.000001 => 0.000001/920 = 1.086956521e-9 sec value of c for nrows =10^4 is nnz=460 and T =0.000038 => 0.000038/920 = 4.1304347826e-8 sec value of c for nrows =10^6 is nnz=460 and T =0.004464 => 0.004464/920 = 4.8521739130e-6 sec value of c for nrows =10^8 is nnz=460 and T =0.442702 => 0.442702/920 = 4.8119782608e-4 sec
```

2. What is the measured performance in total execution time and floating-point operations per second running spvm.c for different sizes nrows = 10², 10⁴, 10⁶ and 10⁸? **Note**: in spmv.c, we set up nrows by setting n = sqrt(nrows). **Hint:** use nnz*2 and the total execution time to calculate the floating-point operations per second in spmv.

```
920/0.000001 = 9200,00,000
920/0.000038 = 242,10,526.3157
920/0.004464 = 2,06,093.1899
920/0.442702 = 2,078.1473767
```

3. What is the main reason for the observed difference between the modeled value and the measured value?

Algorithms are not transformed into performance. Need more insight in hardware

4. What are the <u>read bandwidth values</u> you measure running spvm.c for different sizes nrows = 10², 10⁴, 10⁶ and 10⁸? **Hint:** use nnz (sizeof(double) + sizeof(int)) + nrows (sizeof(double) + sizeof(int)) (slide 11 in here) and the total execution time to calculate the bandwidth of spmv

```
460(12) + 10^2(12) = 6,720 B for 0.000001 sec
for 1 sec 67200.00.000 B => 6720 Mb/sec
```

$$460(12) + 10^{6}(12) = 120,05,520 B for 0.004464 sec$$

for 1 sec 26894,08,602.150538 B => 2689.408 Mb/sec

$$460(12) + 10^{8}(12) = 12000,05,520 B for 0.442702 sec$$

for 1 sec 27106,39,482.089532 B => 2710.63 Mb/sec

5. What is the bandwidth you obtain by running the <u>STREAM benchmark</u> on your system? How does it compare to the bandwidth you measured in spvm? Compile the benchmark with:

Function	Best Rate I	MB/s Avg tin	ne Min tim	e Max time
Copy:	18628.4	0.008619	0.008589	0.008693
Scale:	11916.3	0.013492	0.013427	0.013547
Add:	13461.3	0.017887	0.017829	0.017963
Triad:	13559.4	0.017760	0.017700	0.017816

The difference is assumed to be in the ratio 1:3.5 comparing 5k and 18k

EXERCISE-2:

Questions:

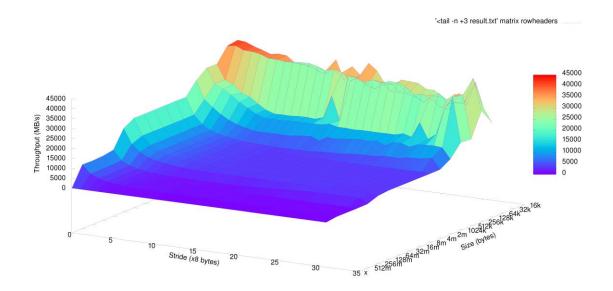
1. Report the name of the processor and the size of the L1, L2, and L3 of the processor you are benchmarking. You can check the specs of your processor online.

L1 - 64kb per core

L2 - 256 kb per core

L3 - 24 mb shared

- 2. Create the memory mountain following the steps above.
 - Save the image of the displayed "memory mountain", and place the resulting image in your pdf file.



- 3. What region (array size, stride) gets the most **consistently** high performance? (Ignoring spikes in the graph that are noisy results...)
 - o What is the read bandwidth reported?

L1 Cache has high performance (stride 2 to 8, size 16k to 64k)

16k to 64k

- 4. What region (array size, stride) gets the most **consistently** low performance? (Ignoring spikes in the graph that are noisy results...)
 - o What is the read bandwidth reported?

Main memory (stride 9 to 32, size 1024k to 512m)

1024k to 512m

- 5. When you look at the graph for stride=1, you (should) see relatively high performance compared to stride=32. This is true even for large array sizes that are much larger than the L3 cache size.
 - How is this possible, when the array cannot possibly all fit into the cache? Your explanation should include a brief overview of hardware prefetching as it applies to caches.

Loads and stores from caches are usually faster compared to main memory. The caches are usually of small size (hardware limitation) i.e L1-64kb, L2-256kb and L3-24mb. Lower the size, faster the access time. If the size if the matrix does not fit in cache, compiler fails to manage spatial locality to it.

Therefore it will be fit into main memory. For example, time to access from main memory for transpose will be n^2(r+Lw). where L is elements per cache line.

6. What is temporal locality? What is spatial locality?

Temporal locality - Reusing data is called temporal locality. In the below example we can say that there is no temporal locality because both the load and store are never used again.

```
Example:
```

```
loop1{
    loop2{
        a[i] = b[j];
    }
}
```

Spatial Locality: Using nearby data is called spatial locality. Assume the array being accessed is a[1,2,3,4,5,6,7]. If 1 is accessed in the array it is highly likely that other elements are accessed from the array. Therefore, all the elements are loaded into cache thereby increasing the performance.

- 7. Adjusting the total array size impacts temporal locality why?
 - Will an increased array size increase or decrease temporal locality?

If increased it will be increases. If decreased it will be decreased. If the array reused is adjusted, the temporal locality will adapt to these changes.

- 8. Adjusting the read stride impacts spatial locality why?
 - Will an increased read stride increase or decrease spatial locality?

If increased it will be increases. If decreased it will be decreased. If the array reused is adjusted, the spatial locality will adapt to these changes.

EXERCISE-3:

Questions:

Question: How do we switch the compiler environment on Beskow?

module swap PrgEnv-cray PrgEnv-gnu

1. Compiler the program in GNU environment with optimization flag -02 and execute it.

1. **Question**: what is the average running time?

0.00000000 s

2. **Question**: Increase N and compile the code, what is the average running time now?

0.00000000 s

3. Get the assembly instructions with

Question: why is the execution time like that? Answer this question using the information you find in the assembly code.

Since the arrays inside the loops are not used later in the code, the compiler ignores that line during execution. This is the problem with smart compilers when optimizing the code. This reflects in assembly instructions.

O2 refers to optimization for code size and execution time. Which means this option increases both compilation time and the performance of the generated code. Therefore we can see improved time for execution of code. As per assembly level code, we cannot observer the loop iterations and floating point operations on a and b.

4. **Question**: What is the average execution time without -02 compilation flag?

N = 5k

1st observation - 0.00002408 s

2nd observation - 0.00002503 s

3rd observation - 0.00002789 s

4th observation - 0.00002813 s

5th observation - 0.00002313 s

6th observation - 0.00002384 s

Average value = 0.00002535 s

2. Check the tick (clock granularity) on Beskow or your local computer.

Question: What is the clock granularity on Beskow?

The clock granularity is 9.54e-07 s

Question: What is the clock granularity when using the RDTSC timer?

The clock granularity is 8.96e-09 s

Question: What is the minimum and average run times? Run the tests multiple times to avoid interference.

N=5k

1st observation - 0.00002694 s

2nd observation - 0.00002599 s

3rd observation - 0.00002789 s

4th observation - 0.00003099 s

5th observation - 0.00002480 s

6th observation - 0.00002503 s

EXERCISE-4:

Questions:

EVENT NAME	MSIZE = 64 Naive
Elapsed time _ (seconds)	0.000808
Instructions per cycle	6.52
L1 cache miss ratio	N/A
L1 cache miss rate PTI	N/A
LLC cache miss ratio	0.08245
LLC cache miss rate PTI	82.455

EVENT NAME	MSIZE = 1000 Optimised
Elapsed time (seconds)	1.601681
Instructions per cycle	0.82
L1 cache miss ratio	3.1071e-5
L1 cache miss rate PTI	31.0750
LLC cache miss ratio	0.52136
LLC cache miss rate PTI	521.364

EVENT NAME	MSIZE = 1000 Naïve
Elapsed time (seconds)	7.403300
Instructions per cycle	1.36
L1 cache miss ratio	0.105632
L1 cache miss rate PTI	105.63278
LLC cache miss ratio	0.00202
LLC cache miss rate PTI	2.02581

EVENT NAME	MSIZE = 64 Optimized
Elapsed time (seconds)	0.000276
Instructions per cycle	0.21
L1 cache miss ratio	N/A
L1 cache miss rate PTI	N/A
LLC cache miss ratio	0.37844
LLC cache miss rate PTI	378.443

Question: What are the factors that impact the most the performance of the matrix multiply operation for different matrix sizes and implementations (naive vs optimized)?

The smaller matrices are usually faster than larger matrices. With size of matrix, memory operations computation time increases which in turn increases time. To improve performance of larger matrices cache blocking (strip mining) is a good idea. However. For smaller matrices this is not good since it has lot of overhead like loops etc.

O2 refers to optimization for code size and execution time. Which means this option increases both compilation time and the performance of the generated code. Therefore, we can see improved time for execution of code. As per assembly level code, we cannot observer the loop iterations and floating-point operations on a and b.

EXERCISE-5:

Questions:

EVENT NAME	N=2049
Elapsed time (seconds)	4.03*10^-2
Bandwidth/Rate (from the code and not PERF)	2.03e+03 Mb/sec
Instructions per cycle	0.14
L1 cache miss ratio	1.17803
L1 cache miss rate PTI	1178.03
LLC cache miss ratio	0.2980
LLC cache miss rate PTI	298.078

EVENT NAME	N=2048	
Elapsed time (seconds)	4.21*10^-2	
Bandwidth/Rate (from the code and not PERF)	7.69e+02 Mb/sec	
Instructions per cycle	0.11	
L1 cache miss ratio	1.1671	
L1 cache miss rate PTI _	1166.17	
LLC cache miss ratio	0.1249	

LLC cache miss rate PTI	124.987

EVENT NAME	N=128
Elapsed time (seconds)	2.09*10^-5
Bandwidth/Rate (from the code and not PERF)	6.76e+02 Mb/sec
Instructions per cycle	2.62
L1 cache miss ratio	N/A
L1 cache miss rate PTI	N/A
LLC cache miss ratio	0.1239
LLC cache miss rate PTI	123.954

EVENT NAME	N=64
Elapsed time (seconds)	2.38*10^-6
Bandwidth/Rate (from the code and not PERF)	1.49e+04 Mb/sec
Instructions per cycle	1.67
L1 cache miss ratio	N/A
L1 cache miss rate PTI	N/A
LLC cache miss ratio	0.3461
LLC cache miss rate PTI	346.119

• What are the factors that impact the most the performance of the transpose operation for different matrix sizes and implementations?

When compiler fails to manage spatial locality, it effects the performance. For larger matrices, there is a larger memory requirement, therefore it requires space in main memory since it wont fit in caches. However, some techniques such as strip-mining, loop unrolling sounds reasonably will to enhance the performance of large matrices.

• Which code transformations can be used in the code for the matrix transpose to improve the re-usage of cache?

EXERCISE-6:

Questions:

- Find out how to request your compiler, e.g. gcc, Cray compiler ... apply vectorization by checking on-line resources. For some systems and compilers, vectorization is the default with certain optimization flags.
 - Find out which optimation flag for your compiler includes vectorization.

```
gcc -O2 -ftree-vectorize transpose.c -O2 -o transpose.out
Works for Optimizations 1 to 5
```

- Find out how you can get a report from the compiler about its success at vectorization.
 - In particular, find out which compiler flag enables a vectorization report for your compiler.

```
gcc -O2 -ftree-vectorize -fopt-info-vec=result.txt transpose.c -O2 -o transpose.out
```

- Read your compiler's documentation to find out what special directives or command-line options can affect vectorization
- Obtain the vectorization report for the <u>matrix-matrix multiply code</u> for MSIZE = 1000.
 - Which lines of the code are not vectorized if any, and in case why the compiler is not vectorizing them?

- matrix_multiply.c:19:31: note: not vectorized: no grouped stores in basic block.
- matrix_multiply.c:26:3: note: not vectorized: loop contains function calls or data references that cannot be analyzed
- matrix_multiply.c:27:5: note: not vectorized: loop contains function calls or data references that cannot be analyzed
- matrix_multiply.c:29:33: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:27:5: note: not vectorized: no grouped stores in basic block.
- matrix_multiply.c:26:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:33:1: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:39:3: note: not vectorized: multiple nested loops.
- matrix_multiply.c:41:7: note: not vectorized: no vectype for stmt: vect__3.41_23 = MEM[(double *)vectp_matrix_b.39_8];
- scalar type: vector(2) double
- matrix_multiply.c:41:7: note: not vectorized: no grouped stores in basic block.
- matrix_multiply.c:41:7: note: not vectorized: no vectype for stmt: MEM[(double *)vectp matrix r.45 52] = vect 5.43 48;
- scalar type: vector(2) double
- matrix_multiply.c:41:7: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:41:7: note: not vectorized: no vectype for stmt: vect_matrix_r_I_I_lsm.35_19 = MEM[(double *)vectp matrix r.33 33];
- matrix_multiply.c:41:7: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:39:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:39:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:46:1: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:41:7: note: not vectorized: no grouped stores in basic block.
- matrix_multiply.c:41:7: note: not vectorized: no vectype for stmt: MEM[(double *)vectp_matrix_r.127_153] = vect__27.125_149;
- scalar type: vector(2) double
- matrix_multiply.c:41:7: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:41:7: note: not vectorized: no vectype for stmt: vect_matrix_r_I_I_lsm.117_34 = MEM[(double *)vectp matrix r.115 46];
- scalar type: vector(2) double
- matrix_multiply.c:41:7: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:39:3: note: not vectorized: not enough datarefs in basic block.

- matrix_multiply.c:39:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:60:5: note: not vectorized: no grouped stores in basic block.
- matrix_multiply.c:41:7: note: not vectorized: no vectype for stmt: vect 36.109 58 = MEM[(double *)vectp matrix b.107 60];
- scalar type: vector(2) double
- matrix_multiply.c:41:7: note: not vectorized: no grouped stores in basic block.
- matrix_multiply.c:41:7: note: not vectorized: no vectype for stmt: MEM[(double *)vectp matrix r.113 137] = vect 38.111 4;
- scalar type: vector(2) double
- matrix_multiply.c:41:7: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:41:7: note: not vectorized: no vectype for stmt: vect_matrix_r_I_I_lsm.103_79 = MEM[(double *)vectp matrix r.101 86];
- scalar_type: vector(2) double
- matrix_multiply.c:41:7: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:39:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:39:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:71:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:60:5: note: not vectorized: no grouped stores in basic block.
- matrix_multiply.c:53:5: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:52:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:79:3: note: not vectorized: not enough datarefs in basic block.
- matrix_multiply.c:79:3: note: not vectorized: not enough datarefs in basic block.

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