Squeezing GPU performance

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GPU peak performance vs. CPU

Peak Double Precision FLOPS

- GPU: 3000 GFLOPS
- CPU: 500 GFLOPS

Peak Memory Bandwidth

- GPU 6x faster on “double”:
  - GPU: 7 GHz x 48 bytes = 336 GB/s.
  - CPU: 2 GHz x 32 bytes = 64 GB/s.

Let’s make a Malaga - Madrid travel (500 km)

- Effective time using the train:
  - Preliminaries: 3 minutes.
  - Travel: 2 hours, 3 minutes.
  - Closing: 2 minutes.
  - TOTAL: 2 hours, 35 minutes.

- Effective time using the plane:
  - Preliminaries: 90 minutes.
  - Travel: 50 minutes.
  - Closing: 30 minutes.
  - TOTAL: 2 hours, 50 minutes (and you are away from downtown!)

The real speed of my car

- Maximum: 250 km/h.
- Average on a 10 years use: 50 km/h.
- So I regularly use my car at 20% of peak performance. Should I be disappointed?
Instructions for the game available on the web site: http://cms.ac.uma.es/kepler

CUDA challenge

Manual Ujáldón @ NVIDIA

Instructions
- The game
- The input data set
- How to play
- Frequently asked questions

Using GPUs
- AT UMA
- In the cloud
- At home

The quiz
- Participants
- Higher score
- The winner strategy

For all loop execution versus data-dependent parallelism

The simplest possible parallel program:
- Loops are parallelizable.
- Workload is known at compile-time.

```c
for (i=0; i<N; i++)
  for (j=0; j<ElementsOnRow[i]; j++)
    convolution (i, j);
```

The simplest impossible parallel program:
- Workload is unknown at compile-time.
- The challenge is data partitioning.

```c
for (i=0; i<N; i++)
  for (j=0; j<ElementsOnRow[i]; j++)
    convolution (i, j);
```

How you represent a sparse matrix in a Compressed Column Format

Example for a 5x5 matrix:

```
1  27  61  2  87  75  3  11  4  33  52
2  75  11  3  2  87  61  11  11  33  42
3  61  11  3  2  87  61  11  11  33  42
4  27  75  11  3  2  87  61  11  11  33  42
5  27  75  11  3  2  87  61  11  11  33  42
```

<table>
<thead>
<tr>
<th>Row indices</th>
<th>colptr</th>
<th>value</th>
<th>as traversed vertically</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>27</td>
<td>1 3 5 2 3 4 5 2 4</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>61</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>11</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>33</td>
<td>33</td>
<td></td>
</tr>
</tbody>
</table>

```
colptr  0 3 4 6 7 9
value  27 75 61 11 11 33 42 87 21
```

All loops are fully parallel.
- Workload is unknown at compile-time.
- The challenge is data partitioning:
  - Deploy streams, kernels, blocks and threads wisely.

A challenge for CUDA programmers around the world: Performed on 8 countries so far

What the program does: Iterate in parallel on each element of a sparse matrix compressed by columns.

- The sparse matrix may have N=100 or N=200 columns, each with a different number of nonzero elements. "numops" operations are performed on each element:

```c
for (i=0; i<N; i++)
  for (j=colptr[i]; j<colptr[i+1]; j++)
    for (k=0;k<numops;k++)
      value[j] += value[j];
```

All loops are fully parallel.
- Workload is unknown at compile-time.
- The challenge is data partitioning:
  - Deploy streams, kernels, blocks and threads wisely.
Input sparse matrices (taken from the Matrix Market collection)

<table>
<thead>
<tr>
<th>Application area</th>
<th>Matrix rows</th>
<th>Matrix columns</th>
<th>Nozeros</th>
<th>Workload</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economics</td>
<td>300</td>
<td>100</td>
<td>22,000</td>
<td>Base</td>
</tr>
<tr>
<td>Demography</td>
<td>6,000</td>
<td>100</td>
<td>440,000</td>
<td>20 x Base</td>
</tr>
<tr>
<td>Oceanography</td>
<td>24,000</td>
<td>100</td>
<td>1,760,000</td>
<td>160 x Base</td>
</tr>
<tr>
<td>Quantum physics</td>
<td>96,000</td>
<td>100</td>
<td>7,040,000</td>
<td>2560 x Base</td>
</tr>
<tr>
<td>Linear algebra</td>
<td>200</td>
<td>200</td>
<td>27,000</td>
<td>Base</td>
</tr>
<tr>
<td>Image processing</td>
<td>4,000</td>
<td>200</td>
<td>540,000</td>
<td>20 x Base</td>
</tr>
<tr>
<td>Astrophysics</td>
<td>32,000</td>
<td>200</td>
<td>4,320,000</td>
<td>160 x Base</td>
</tr>
<tr>
<td>Biochemistry</td>
<td>512,000</td>
<td>200</td>
<td>69,120,000</td>
<td>2560 x Base</td>
</tr>
</tbody>
</table>

And you have to choose the winner parallelization strategy

1: Thread-level parallelism (TLP)
2: Instruction-level parallelism (ILP)
3: Data parallelism (SIMD)
4: Vectorial (warp = 32)

Example strategy:
- We launch a CUDA kernel for each matrix column.
- Each kernel will have the lowest number of blocks.
- Each kernel will have the largest number of warps.
- Each thread will be as thin as possible (computes on a single elem.)

You can try different operands and operators

Sparse matrices processing

What each thread does:

```cpp
int float double value[numelements];
for all elements assigned to each thread:
  for numops. to be done on each element
    value[i] *= value[i];
```

Changing the operator to lighter (addition) or heavier (division) will also have an impact depending on the time spent to perform each operation (its latency).

The way we create streams. An example of 3 streams, each composed of 3 kernels

```cpp
__global__ kernel_A(pars) {body} // Same for B...Z
cudaStream_t stream_1, stream_2, stream_3;
...
cudaStreamCreateWithFlags(&stream_1, ...);
cudaStreamCreateWithFlags(&stream_2, ...);
cudaStreamCreateWithFlags(&stream_3, ...);
...
kernel_A <<< dimgridA, dimblockA, 0, stream_1 >>> (pars);
kernel_B <<< dimgridB, dimblockB, 0, stream_1 >>> (pars);
kernel_C <<< dimgridC, dimblockC, 0, stream_1 >>> (pars);
...
kernel_P <<< dimgridP, dimblockP, 0, stream_2 >>> (pars);
kernel_Q <<< dimgridQ, dimblockQ, 0, stream_2 >>> (pars);
kernel_R <<< dimgridR, dimblockR, 0, stream_2 >>> (pars);
...
kernel_X <<< dimgridX, dimblockX, 0, stream_3 >>> (pars);
kernel_Y <<< dimgridY, dimblockY, 0, stream_3 >>> (pars);
kernel_Z <<< dimgridZ, dimblockZ, 0, stream_3 >>> (pars);
```
Top 10 optimizations performed by students

1. Increase the number of operations per element (1024).
2. Increase the sparse matrix size (up to 69M nonzeros).
3. Change the operator (add/sub/mul/div).
4. Change the operand (int/float/double).
5. Tune the CUDA block size (384 threads per block).
6. Group blocks in kernels and those in streams to express more parallelism.
7. Optimize memory access using shared memory and regs.
8. Guide the compiler via \texttt{#pragma unroll} directives.
9. Enable the fused multiply-add operator.
10. Use vector instructions to exploit (x,y,z,w) and (r,g,b,a).

Performance attained on a GeForce GTX480 (peak performance 1330 GFLOPS on 32-bit)

<table>
<thead>
<tr>
<th>Optimization</th>
<th>Acceler.</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Increase the number of operations per element (up to 1024)</td>
<td>250.00 x</td>
<td>0.20 GFLOPS</td>
</tr>
<tr>
<td>2. Use a bigger sparse matrix (up to 69,120,000 nonzeros)</td>
<td>116.35 x</td>
<td>23.27 GFLOPS</td>
</tr>
<tr>
<td>3. Choose the sum operator (add)</td>
<td>1.00 x</td>
<td>23.27 GFLOPS</td>
</tr>
<tr>
<td>4. Replace the double operand (64-bits) by float (32-bit)</td>
<td>1.89 x</td>
<td>44.00 GFLOPS</td>
</tr>
<tr>
<td>5. Tune the block size (384 threads)</td>
<td>1.00 x</td>
<td>44.00 GFLOPS</td>
</tr>
<tr>
<td>6. Group kernels in streams</td>
<td>1.00 x</td>
<td>44.00 GFLOPS</td>
</tr>
<tr>
<td>7. Optimize memory accesses using shared memory and registers</td>
<td>3.19 x</td>
<td>140.75 GFLOPS</td>
</tr>
<tr>
<td>8. Unroll the loop via a \texttt{#pragma unroll} compiler directive</td>
<td>4.07 x</td>
<td>573.95 GFLOPS</td>
</tr>
<tr>
<td>9. Enable the FMADD (fused multiply-add) operator</td>
<td>2.15 x</td>
<td>1236.58 GFLOPS</td>
</tr>
<tr>
<td>10. Enable vector processing on computational sentences (4 in 1)</td>
<td>1.00 x</td>
<td>1236.58 GFLOPS</td>
</tr>
<tr>
<td>1.2 Saturate the number of operations (up to 1M)</td>
<td>1.02 x</td>
<td>1260.00 GFLOPS</td>
</tr>
<tr>
<td>8.2 Saturate the loop unroll factor (until 4096)</td>
<td>1.01 x</td>
<td>1280.00 GFLOPS</td>
</tr>
<tr>
<td>2.2 Generate a huge matrix to exploit GPU scalability</td>
<td>1.02 x</td>
<td>1310.00 GFLOPS</td>
</tr>
<tr>
<td>2.3 Tune the matrix to match the structure of CUDA parallelism</td>
<td>1.01 x</td>
<td>1330.00 GFLOPS</td>
</tr>
</tbody>
</table>