High Performance Computing Modernization Program (HPCMP) Summer 2011 Puerto Rico Workshop on Intermediate Parallel Programming & Cluster Computing

in conjunction with
the National Computational Science Institute (NCSI)/
SC11 Conference
S.V. Providence
Jointly hosted at
Polytechnic U of Puerto Rico
and U Oklahoma
and available live via videoconferencing
(streaming video recordings coming soon)

Sponsored by
DOD HPCMP,
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HPCMP

PUPR-IPPCC 2011
LN1: CUDA Overview

S.V. Providence

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Polytechnic University of Puerto Rico
Intermediate Parallel Programming & Cluster Computing,
Thursday, Aug. 4th, 2011

Outline

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- Introduction
- GPU Hardware
- Programming Model
- Conclusion

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- Programmable
- Can be installed in most desktops

Figure: Tesla C1060

- Central to the second fastest computer on Earth (top500.org)
- Similar in price to CPU

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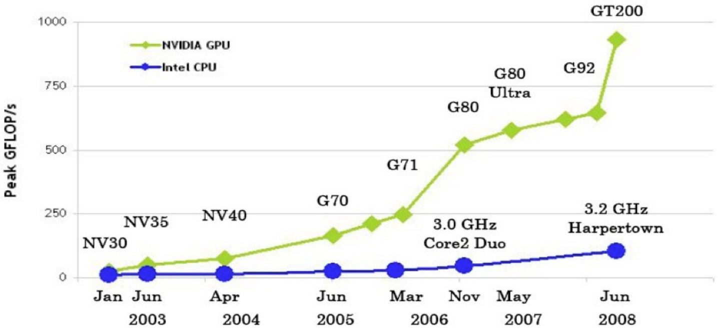
Introduction
Performance

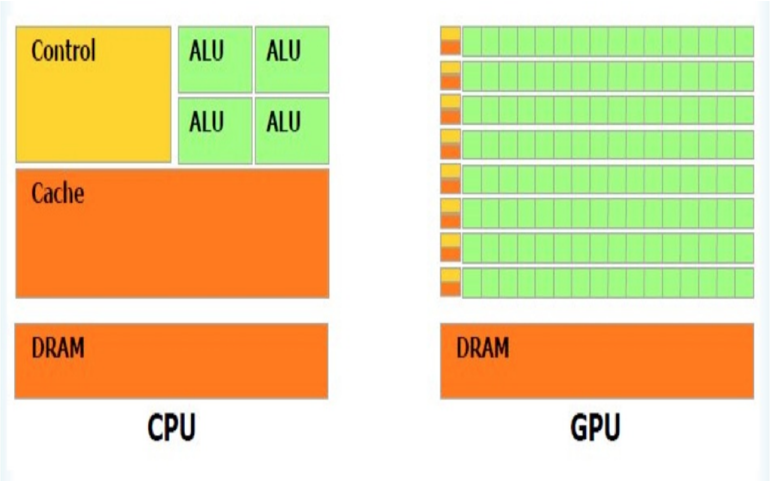


GT200 = GeForce GTX 280	G71 = GeForce 7900 GTX	NV35 = GeForce FX 5950 Ultra
G92 = GeForce 9800 GTX	G70 = GeForce 7800 GTX	NV30 = GeForce FX 5800
G80 = GeForce 8800 GTX	NV40 = GeForce 6800 Ultra	

Figure: nvidia.com

GPU H/W

μ-processor structure



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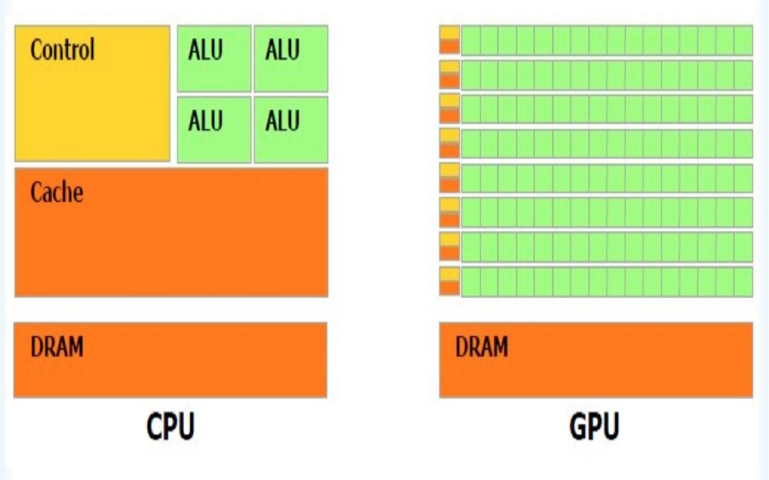

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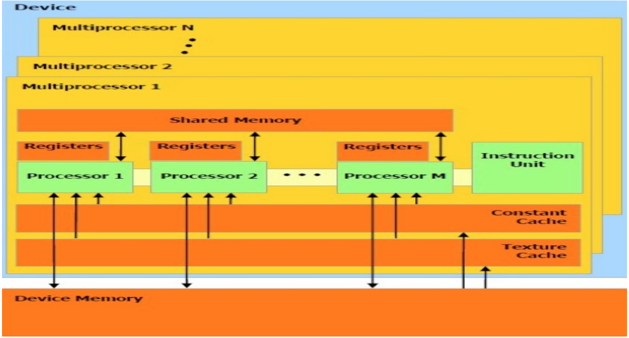

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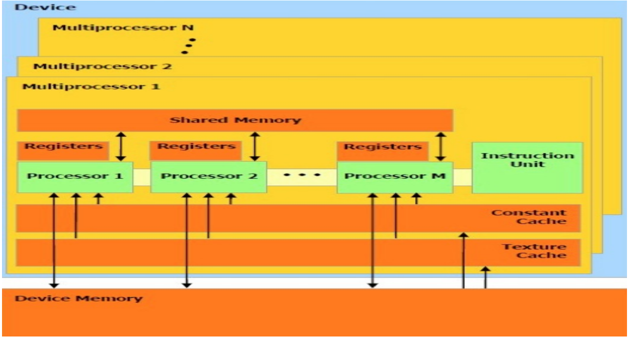

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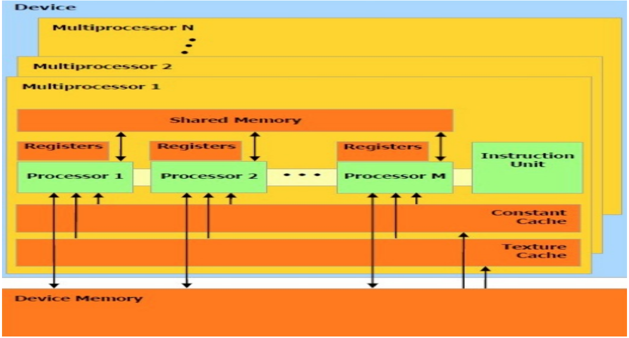

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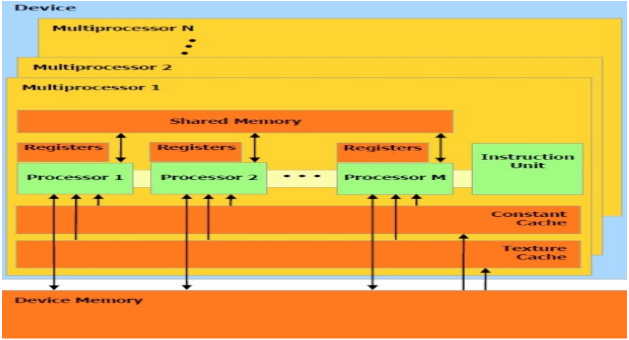

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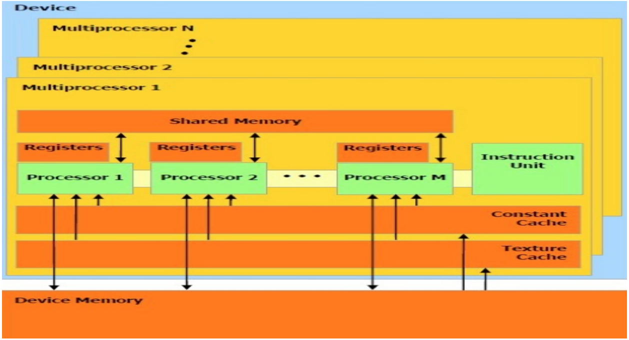

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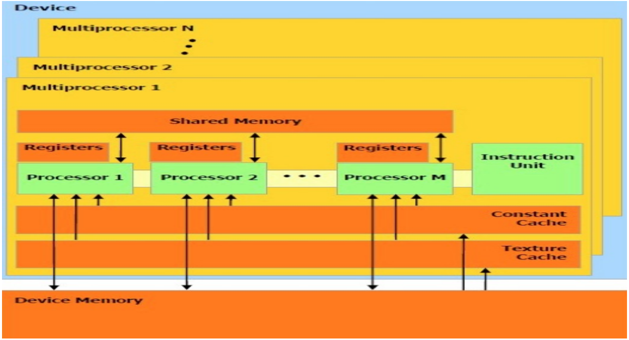

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- 933 GFLOPS peak performance
- 10 thread processing clusters (TPC)
- 3 multiprocessors per TPC
- 8 cores per multiprocessor
- 16384 registers per multiprocessor
- 16 KB shared memory per multiprocessor
- 64 KB constant cache per multiprocessor
- 6 KB < texture cache < 8 KB per multiprocessor
- 1.3 GHz clock rate
- Single and double-precision floating-point calculation
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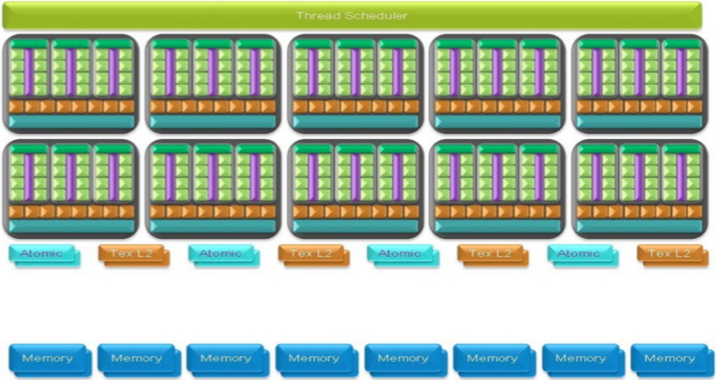
- thread processing clusters
- atomic Tex L2
- Memory



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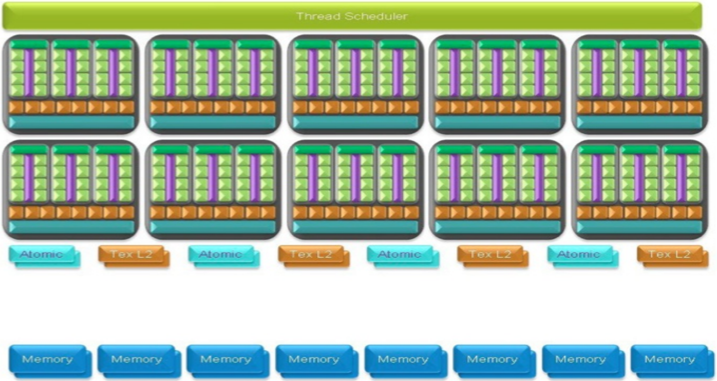

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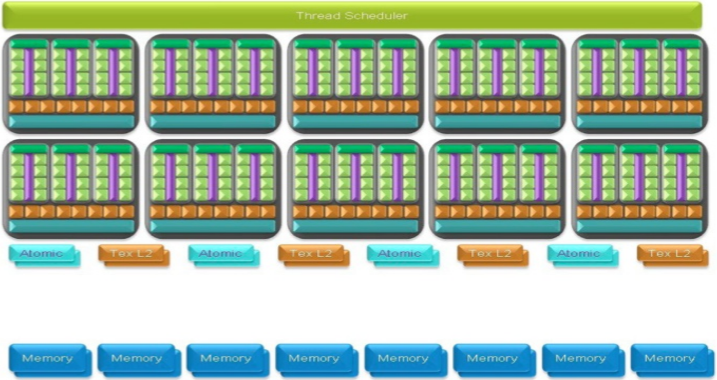

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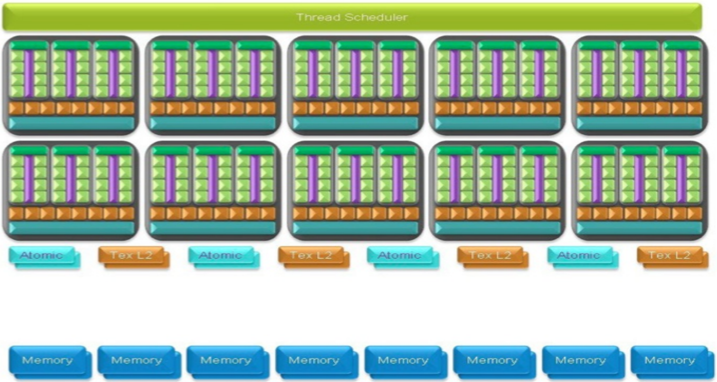

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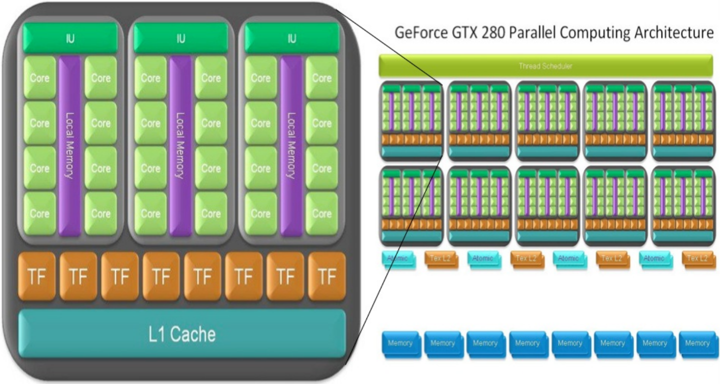
- IU - instruction unit



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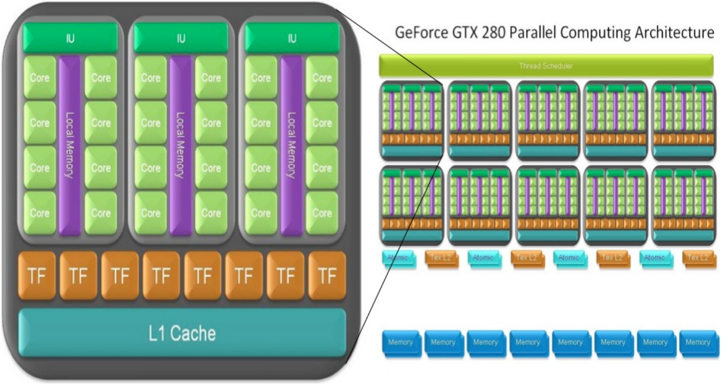

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GPU H/W
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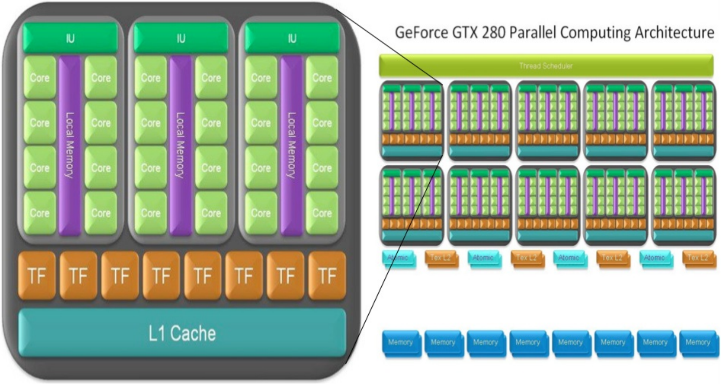

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- Power consumption is based on utilization
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  - Blu-ray DVD playback mode: 35 W
  - Full 3D performance mode: worst case 236 W ? HybridPower mode: 0 W
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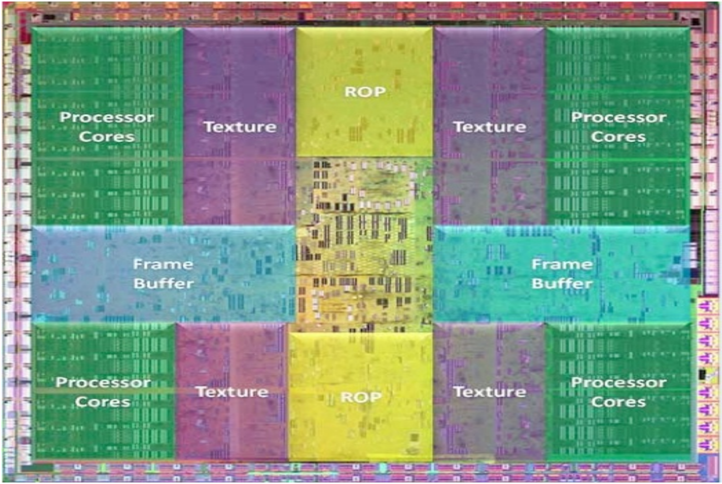
GPU H/W
240 core GPU image



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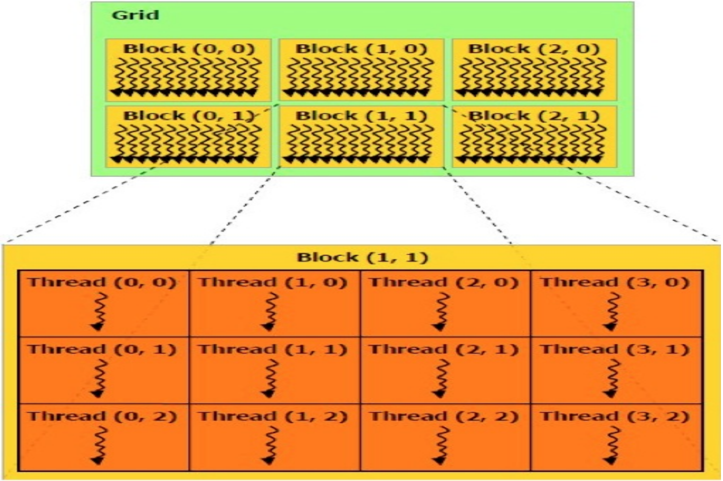

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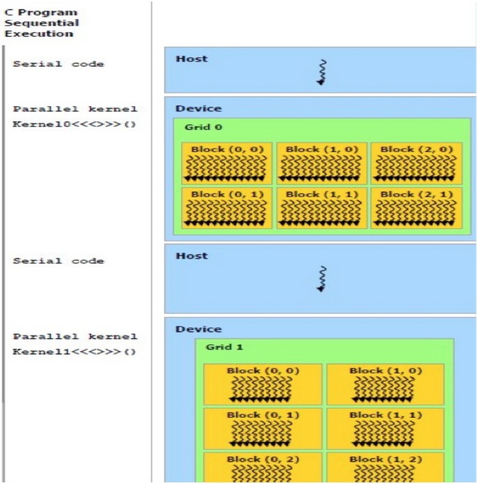

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Programming Model
GPU vs. CPU

CPU C program

```
void add_matrix_cpu
            (float *a, float *b, float *c, int N)
{
     int i, j, index;
    for (i=0;i<N;i++) {
     for (j=0;j<N;j++) {
        index =i+j*N;
        c[index]=a[index]+b[index];
        }
    }
}
void main()
{
  .....
      add_matrix(a,b,c,N);
}
```

CUDA C program

```
__global__ void add_matrix_gpu
            (float *a, float *b, float *c, int N)
{
    int i=blockIdx.x*blockDim.x+threadIdx.x;
    int j=blockIdx.y*blockDim.y+threadIdx.y;
    int index =i+j*N;
    if( i <N && j <N) c[index]=a[index]+b[index];
}

void main()
{
    dim3 dimBlock (blocksize,blocksize);
    dim3 dimGrid (N/dimBlock.x,N/dimBlock.y);
    add_matrix_gpu<<<dimGrid,dimBlock>>>(a,b,c,N);
}
```

Figure: nvidia.com

Conclusion

- SIMD causes some problems
- GPU computing is a good choice for fine-grained data-parallel programs with limited communication
- GPU computing is not so good for coarse-grained programs with a lot of communication
- The GPU has become a co-processor to the CPU

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For Further Reading I

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