# Attaining High Performance in General-Purpose Computations on Current Graphics Processors

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# Motivation (I)

- GPUs have become the first widely available HPC platform
- Successfully used in linear algebra, image processing, data mining, simulations. . .
- Recently introduced advances:
  - Hardware level: **Unified Architecture**
  - Software level: **CUDA**
- Peak performance up to $10x$ (Core2Duo vs Nvidia 8800)

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# Motivation (II)

- GPUs are specific-purpose processors
- The GPU architecture is focused on graphics performance
- Not every general-purpose algorithm will fit correctly on GPU
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Which algorithms fit better on the graphics processor?

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Impact of the improvements of last generations of GPUs

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# Outline

# Introduction and goals

## Methodology

- Microbenchmarks from BLAS and image processing
- Implement the benchmarks on CPU and both generations of GPUs
- Use only optimized benchmarks on both architectures

## Goals

- Extract the features of GPU-like algorithms through the evaluation of different routines
- Compare both generations of GPU architectures
- Extract the impact of data transfers on both generations
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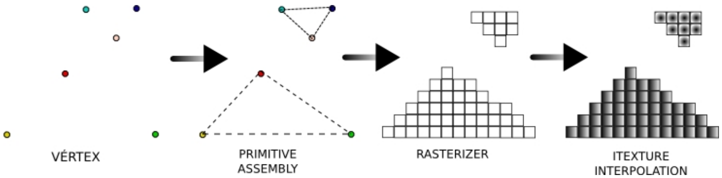
# Classical GPU pipeline




- Each stage of the pipeline works with a different datatype
- Each stage is computed on a different type of processor (vertex processors and fragment processors)
- But the processors are programmable. . .

# Classical GPU overview

## Programmability

- Both vertex processors and fragments processors are programmable
- Usually fragment processors (FP) are programmed
- The replication of FP fits well with data-parallel routines
- SIMD architecture

## Disadvantages

- No memory hierarchy at all
- Just one memory direction could be written for each fragment
- Hard to program (OpenGL + Cg)

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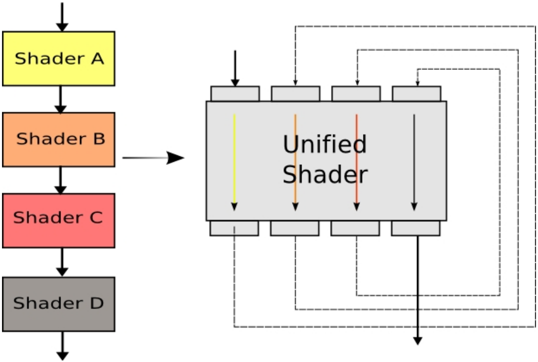
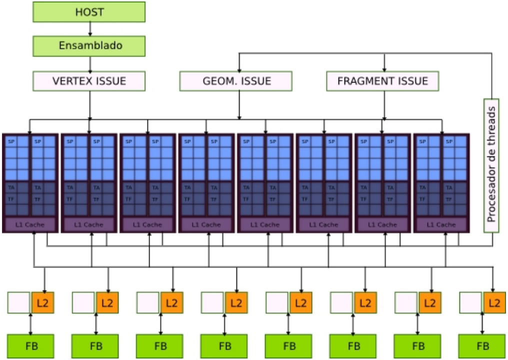
# Unified GPU shader




- One unified shader with multiple functionality
- Works with any type of graphical data
- GPGPU: all programmable shaders are now available

# Unified GPU architecture: G80




**NVIDIA G80**

- Main unified implementation
- Up to 128 cores in the unified shader
- Introduction of memory hierarchy
- Higher clock frequency in the shader
- More flexibility in reading/writing to memory
- CUDA library

# Selection of benchmarks

## Features to be evaluated

1. Data parallelism
2. Input data reutilization
3. Computational intensity per stream element

Routines to be evaluated:

**SGEMM:** $C = \alpha AB + \beta C$

**SGEMV:** $y = \alpha Ax + \beta y$

**SAXPY:** $y = \alpha x + y$

**SSCAL:** $y = \alpha y$

**2D Convolution**

# Features of the benchmarks

- Selected routines:

| Routine | Type | Data parallelism | Input reutilization | Arith. intensity |
|---|---|---|---|---|
| **SGEMM** | BLAS 3 | High | High | High |
| **SGEMV** | BLAS 2 | High | Medium | Medium |
| **SAXPY** | BLAS 1 | High | None | Low |
| **SSCAL** | BLAS 1 | High | None | Lowest |
| **Convolution** | Image | High | Low | Medium |

- Hardware setup:

**Classical architecture**

AMD Athlon 2400+
+
Nvidia Geforce 6200

**Unified architecture**

Intel Core2Duo 1.86 Ghz
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GotoBLAS / CUBLAS 1.0

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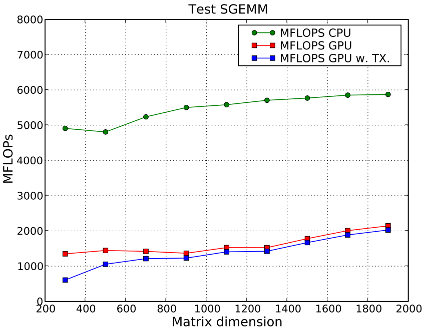
# Results on classical GPUs. SGEMM

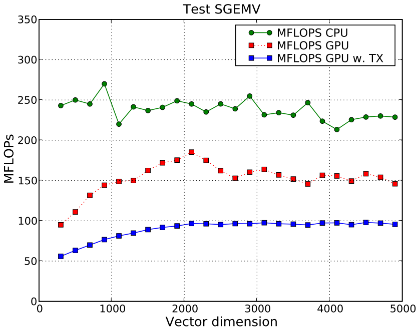



**Data reutilization impact**

- CPU outperforms GPU
- Speedup up to $x4$
- Impact of cache hierarchy on CPU
- Data transfers not significant

- Input data reutilization seems a key factor on GPU
- SGEMV exhibits less input data reutilization...

# Results on classical GPUs. SGEMV



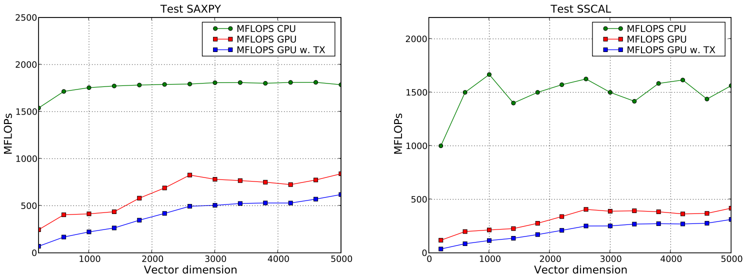

**Data reutilization impact**

- CPU outperforms GPU, but up to $x2$
- Data transfers more significant

Input data reutilization is a key factor on GPU

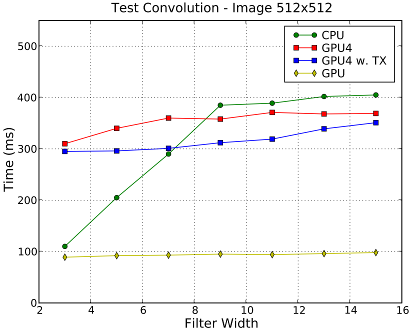
# Results on classical GPUs. SAXPY and SSCAL

## Arithmetic intensity




- SAXPY and SSCAL are stream-oriented operations
- They should attain high performance on GPUs
- However, CPU outperforms GPU for these operations
- Arithmetic intensity per stream element is another key factor

# Results on classical GPUs. Convolution



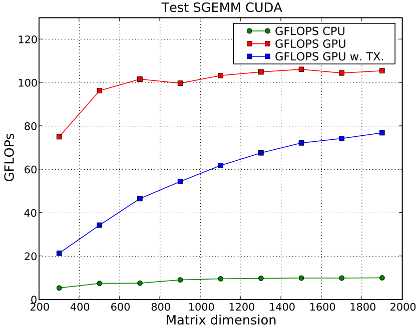

**Convolution performance**

- Attained performance similar to that on CPU
- Optimized implementation for vectorial capabilities (`GPU4`) attains $4x$ speedup

## Required features on GPU

- High data parallelism
- Low input data reutilization
- High arithmetic intensity per stream element

# Results on unified GPUs. SGEMM

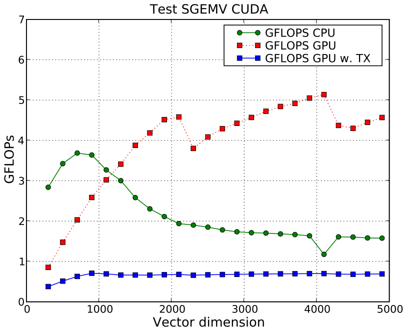



**Data reutilization impact**

- GPU outperforms CPU
- Speedup up to $x10$
- However, only attaining $20\%$ of the peak performance of the GPU
- Data transfers more significant than on previous generations

- Input data reutilization is still important on GPU, but less than on previous generations
- Reason: more sophisticated memory hierarchy

# Results on unified GPUs. SGEMV



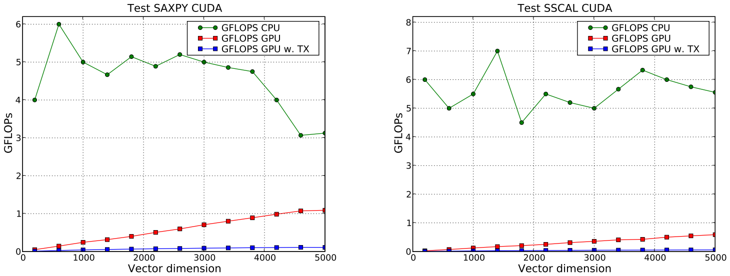

**Data reutilization impact**

- GPU outperforms CPU for big matrices
- Impact of cache hierarchy on CPU: faster for small streams of data
- Data transfers very significant

- Data transfer stage is a very important factor now
- G6 $\rightarrow$ G80 $(x20)$ but AGP $\rightarrow$ PCIExpress $(x2)$
- Modern GPUs work better with big streams of data

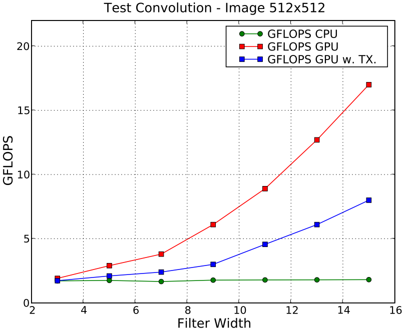
# Results on unified GPUs. SAXPY and SSCAL

## Arithmetic intensity




- However, arithmetic intensity per element is still a key factor
- CPU outperforms GPU for these operations

# Results on unified GPUs. Convolution



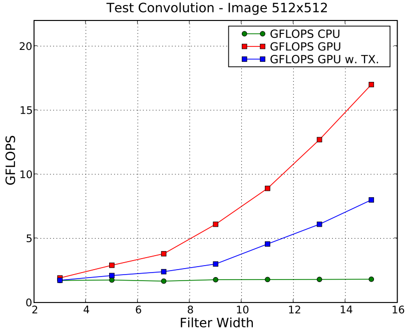

**Convolution performance**

- Attained the highest speedup of the benchmarks
- Highest data transfer impact

## Required features on unified GPUs

- High data parallelism, low reutilization, high intensity
- Low ratio transfer/calculation
- Big data streams

# Results on unified GPUs. Convolution

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# Conclusions

- The GPU is an interesting platform for HPC
- However, not every algorithm extracts all the performance
- Desirable features:
  - High data parallelism
  - Low input data reutilization
  - High arithmetic intensity
  - Operating with big streams of data
- Necessary to design algorithm minimizing data transfers

# Thank you...

**For more information. . .**

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