On Convenience and Inconvenience in GPU Computing

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LANS Seminar







Debunking the 100X GPU vs. CPU Myth: An Evaluation of Throughput Computing on CPU and GPU

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ABSTRACT

Recent advances in computing have led to an explosion in the amount of data being generated. Processing the ever-growing data in a timely manner has made throughput computing an important as the control of parallelism in these kernels which makes them suitable for today's multi-cree CPUs and GPUs. In the past few years there have been many studies claiming GPUs deliver substantial speedups (between 10X and 100X) over multi-cree CPUs on these kernels. To understand where such large performance difference comes from, we perform a rigorous performance analysis and find that after a present and the control of the cont

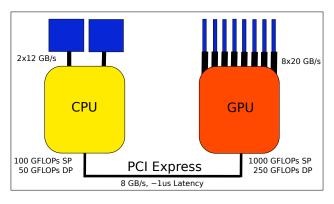
1. INTRODUCTION

The past decade has seen a huge increase in digital content as more documents are being created in digital form than ever before. Moreover, the web has become the medium of choice for storing and delivering information such as stock market data, personal records, and news. Soon, the amount of digital data will exceed exabytes (10%) [31]. The massive amount of data makes storing, cataloging, processing, and retrieving information challenging. A new class of applications has emerged across different domains such as database, games, video, and finance that can process this huge amount of data to distill and deliver appropriate content to users. A distinguishing feature of these applications is that they

Proc. ISCA 2010

GPUs: Disillusion

Computing Architecture Schematic

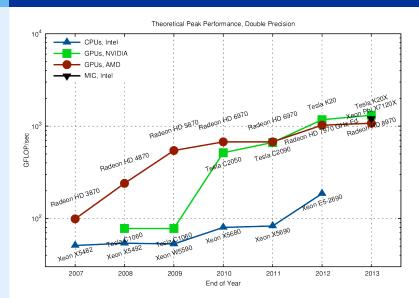


Good for large FLOP-intensive tasks, high memory bandwidth PCI-Express can be a bottleneck

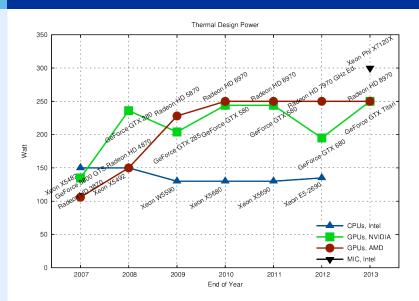
 \gg 10-fold speedups (usually) not backed by hardware



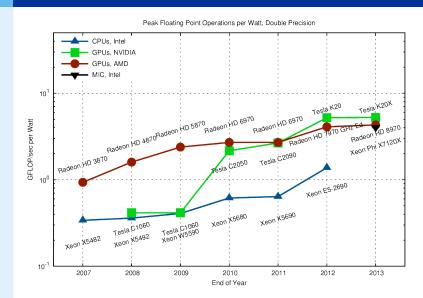
Single Precision Peak GFLOP/sec



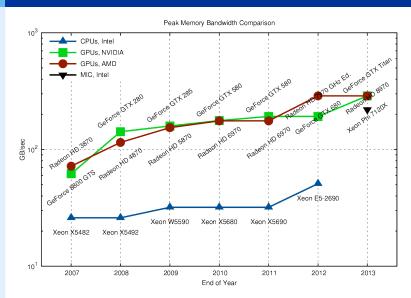
Double Precision Peak GFLOP/sec



Thermal Design Power: 2 CPUs vs. 1 GPU for Fair Comparison



GFLOP/sec per Watt



Memory Bandwidth

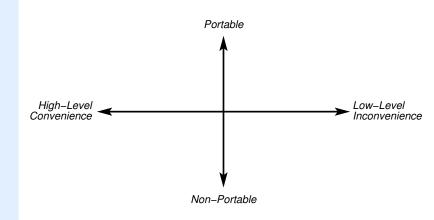
Which Accelerator is Right for Me?

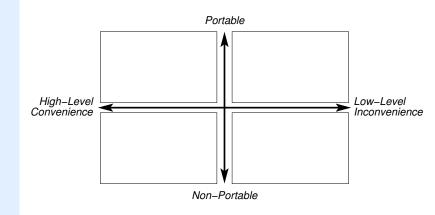
Available Accelerators (Rough Sketch, Theoretical Peaks)

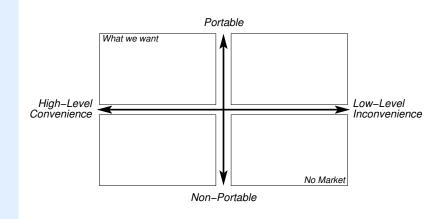
Name	TFLOP/s	RAM (GB)	GB/s	TDP	Price
NVIDIA GTX 580	3.0/~0.2	1.5-3.0	192	244	\$500
NVIDIA GTX Titan	4.5/1.3	6.0	288	250	\$~1k
NVIDIA Tesla 2050	1.3/0.5	3.0-6.0	150	225	\$~2k
NVIDIA K20	3.5/1.2	5.0	200	220	\$~3k
AMD HD 7970	3.5/~0.9	3.0-6.0	264	250	\$400
AMD FirePro W9k	4.0/1.0	6.0	264	274	\$~3k
Intel Xeon Phi	~2.0/~1.0	8.0	320	225	\$~3k
Intel Xeon E5-264x	0.2/0.1	~64	~48	100	\$~1k

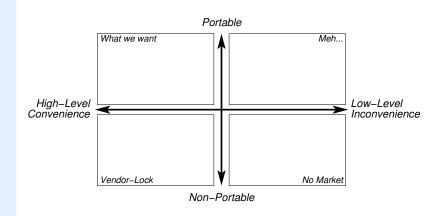
PETSc Considerations

Single precision performance doesn't matter Essentially all kernels memory bandwidth limited Memory access patterns rather irregular









NVIDIA CUDA

```
// GPII kernel:
__global__ void kernel(double *buffer)
  int idx = blockIdx.x * blockDim.x + threadIdx.x;
 buffer[idx] = 42.0;
// host code:
int main()
  . . .
  cudaMalloc((void**)&buffer, size);
  kernel << < blocknum, blockdim>>> (buffer);
  . . .
```

Convenient: Almost no additional code required

Non-Portable: Vendor-lock

Non-Portable: Relies on nvcc being available

NVIDIA CUDA Driver API

Relief: No dependency on nvcc

Inconvenient: Pseudo-Assembly PTX code

Non-Portable: PTX updated with each device generation

NVIDIA CUDA Driver API

```
// Generated by NVIDIA NVVM Compiler
// Compiler built on Sun Aug 19 23:20:45 2012
// Driver 304.43
.version 3.0
.target sm 13, texmode independent
.address size 32
.entrv k0(
 .param .u32 .ptr .global .align 4 _k0_param_0,
 .param .u32 _k0_param_1,
 .param .u32 .ptr .global .align 4 _k0_param_2,
 .param .u32 _k0_param_3,
 .param .u32 .ptr .global .align 4 _k0_param_4,
 .param .u32 _k0_param_5,
 .param .u32 _k0_param_6,
 .param .u32 _k0_param_7,
 .param .u32 .ptr .global .align 4 _k0_param_8,
 .param .u32 _k0_param_9,
```

OpenACC and Friends

```
void func(...) {
  #pragma acc data pcopyin(A[0:size][0:size])
    #pragma acc kernels loop
    for(int i=0; i< size; i++)</pre>
      for(int j=0; j < size; j++)</pre>
        A[i][j] = 42;
int main()
  double A[1337][1337];
  func(A);
```

Convenient: Simple OpenMP-type pragma annotations

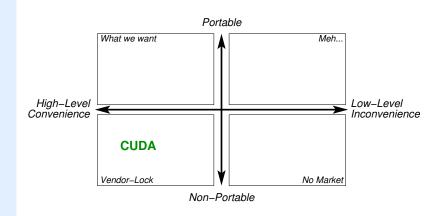
Non-Portable: Compiler support?

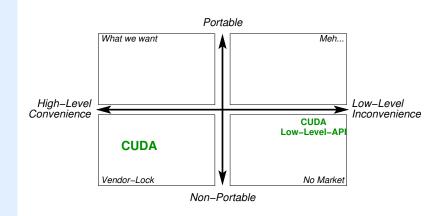
Non-Portable: Insufficient control over memory transfers?

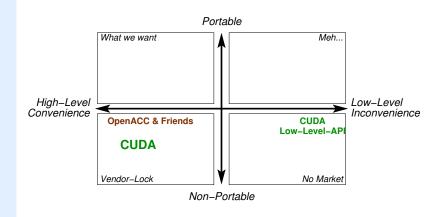
OpenCL

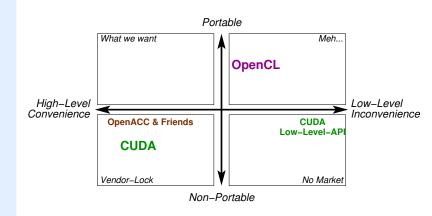
```
const char *kernel string =
"__kernel void mykernel(__qlobal double *buffer) {
 buffer[get global id(0)] = 42.0:
};";
int main() {
  cl program my prog = clCreateProgramWithSource(
         my context, 1, & kernel string, & source len, & err);
  clBuildProgram (my prog, 0, NULL, NULL, NULL, NULL);
  cl kernel my kernel = clCreateKernel (my prog,
                            "mykernel", &err);
  clSetKernelArg(my kernel, 0, sizeof(cl mem), &buffer);
  clEnqueueNDRangeKernel(queue, my kernel, 1, NULL,
                &global size, &local size, 0, NULL, NULL);
```

Inconvenient: Low-level boilerplate code required
Portable: Broad hardware support (separate SDKs)
Bad News: No more development effort from NVIDIA









GPUs: Library Aspects

Challenge: Hardware

Portable performance

Auto-tuning

Testing requires many different machines

Challenge: Memory

Allocation failures?

Multi-GPU?

PCI-Express bottleneck

Challenge: Programming

Kernel language?

Which low-level parameters to expose?

Part 2

Part 2: Basic Linear Algebra

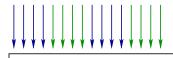
Consider Something Simple

$$x \leftarrow y, x, y \in \mathbb{R}^N$$
, distinct



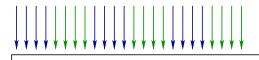
Consider Something Simple

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, distinct



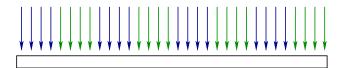
Consider Something Simple

 $x \leftarrow y, x, y \in \mathbb{R}^N$, distinct



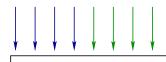
Consider Something Simple

 $x \leftarrow y, x, y \in \mathbb{R}^N$, distinct



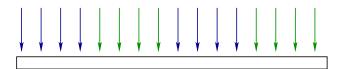
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Consider Something Simple

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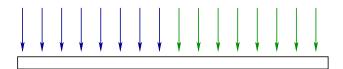
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, distinct



Consider Something Simple

 $x \leftarrow y, x, y \in \mathbb{R}^N$, distinct



Consider Something Simple

 $x \leftarrow y, x, y \in \mathbb{R}^N$, distinct

Usually a simple for-loop, memory-bandwidth limited

Parameters

Data Types: double, double2, etc.

Blocking: Small segments vs. large blocks

Thread sizes: threads per group, number of thread groups

OpenCL Benchmarking Baseline

double

small segments

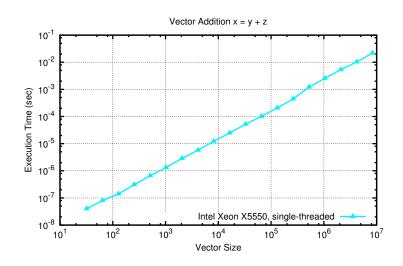
128 threads per work group

128 work groups

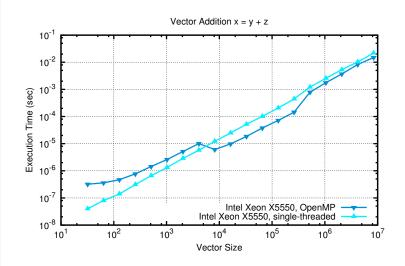
Results (GB/sec)

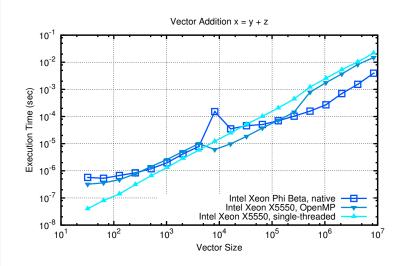
Name	double, small, 128x128	Best	double2, large, 32x240
NVIDIA GTX 285	101	134	134
NVIDIA GTX 580	150	166	123
AMD HD 7970	161	249	140
INTEL E5-2670 x2	32	79	18
INTEL Xeon Phi	32	95	21

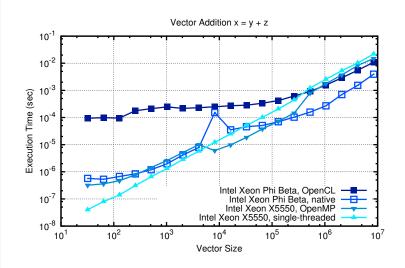
Vector Addition Benchmarks

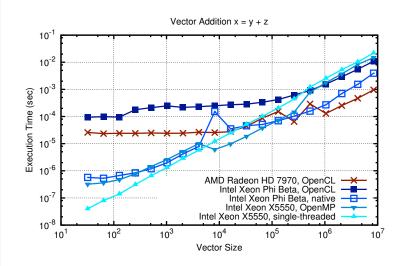


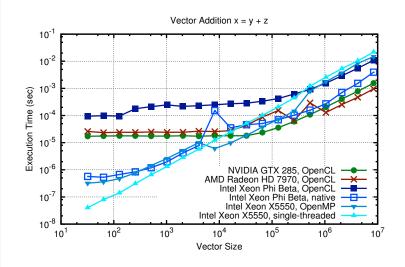
Vector Addition Benchmarks

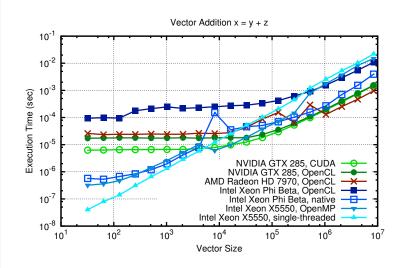












Matrix-Matrix Multiplication

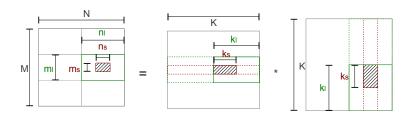
Parameter Space Explosion

Global Block Sizes

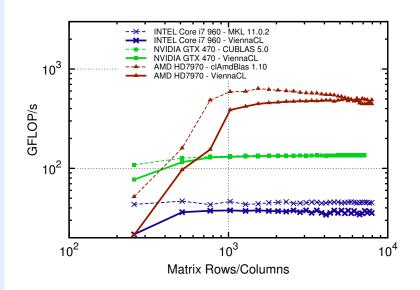
Shared Mem Block Sizes

Thread-Private Block Sizes

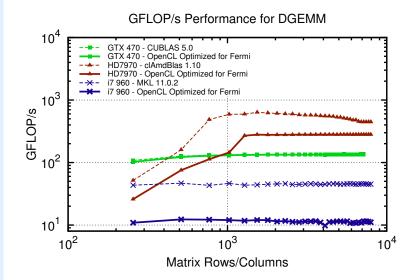
Loop Unrolling



Matrix-Matrix Multiplication



Matrix-Matrix Multiplication

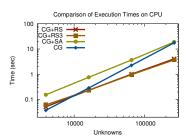


Part 3: Preconditioners

Poisson Equation in 2D

Unstructured triangular grid Finite element discretization

Various Algebraic Multigrid Methods

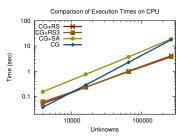


Intel Core i7 960 CPU

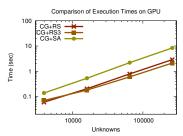
Poisson Equation in 2D

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Intel Core i7 960 CPU

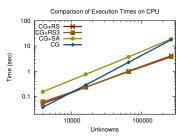


NVIDIA GTX 470 GPU

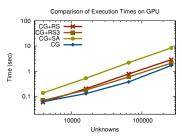
Poisson Equation in 2D

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Various Algebraic Multigrid Methods

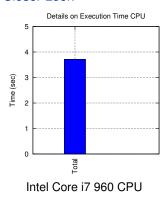


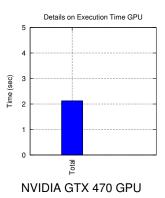
Intel Core i7 960 CPU



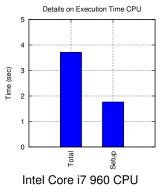
NVIDIA GTX 470 GPU

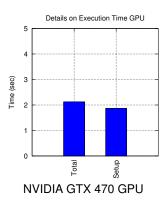
A Closer Look





A Closer Look





Findings

Solver cycle time scales with GPU Setup time limited by $CPU \Rightarrow Minimize$

Basic Idea

Factor sparse matrix $A \approx \tilde{L}\tilde{U}$ $\tilde{\boldsymbol{L}}$ and $\tilde{\boldsymbol{U}}$ sparse, triangular Forward solve $\tilde{\boldsymbol{L}} y = z$ ILU0: Pattern of \tilde{L} , \tilde{U} equal to A Backward solve $\tilde{U}x = y$

Solver Cycle Phase

Residual correction $\tilde{L}\tilde{U}x = z$ ILUT: Keep *k* elements per row Little parallelism in general

Level Scheduling

Build dependency graph

Substitute as many entries as possible simultaneously

Trade-off: Each step vs. multiple steps in a single kernel

Level Scheduling

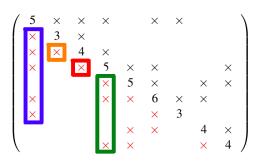
Build dependency graph

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Level Scheduling

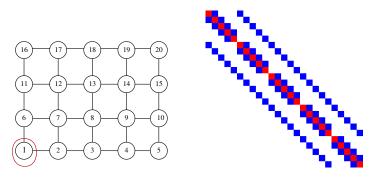
- Build dependency graph
- Substitute as many entries as possible simultaneously
- Trade-off: Each step vs. multiple steps in a single kernel



Interpretation on Structured Grids

2d finite-difference discretization

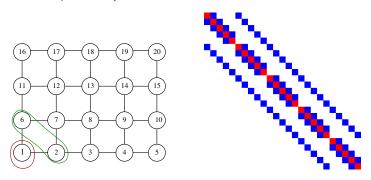
Substitution whenever all neighbors with smaller index computed



Interpretation on Structured Grids

2d finite-difference discretization

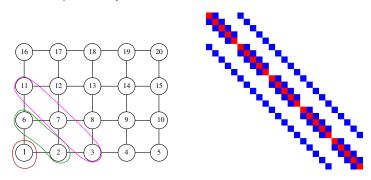
Substitution whenever all neighbors with smaller index computed



Interpretation on Structured Grids

2d finite-difference discretization

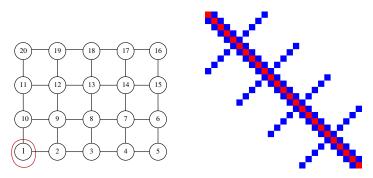
Substitution whenever all neighbors with smaller index computed



Interpretation on Structured Grids

2d finite-difference discretization

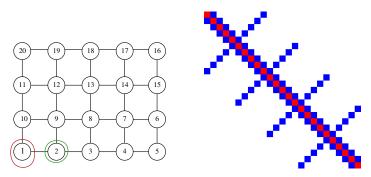
Substitution whenever all neighbors with smaller index computed



Interpretation on Structured Grids

2d finite-difference discretization

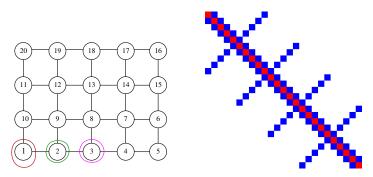
Substitution whenever all neighbors with smaller index computed



Interpretation on Structured Grids

2d finite-difference discretization

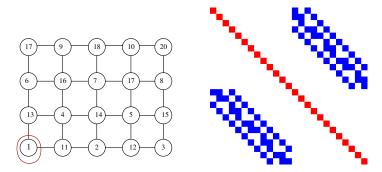
Substitution whenever all neighbors with smaller index computed



Interpretation on Structured Grids

2d finite-difference discretization

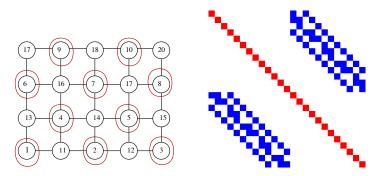
Substitution whenever all neighbors with smaller index computed



Interpretation on Structured Grids

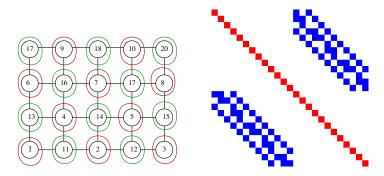
2d finite-difference discretization

Substitution whenever all neighbors with smaller index computed



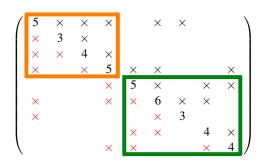
Interpretation on Structured Grids

2d finite-difference discretization
Substitution whenever all neighbors with smaller index computed



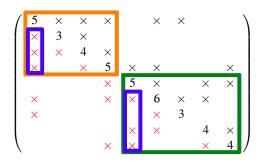
Block-ILU

- Apply ILU to diagonal blocks
- Higher parallelism
- Usually more iterations required (problem-dependent)



Block-ILU

- Apply ILU to diagonal blocks
- Higher parallelism
- Usually more iterations required (problem-dependent)



Benchmark

Benchmark - Setup

Benchmark Setup

Hardware

NVIDIA GTX 580 (default)
AMD HD 7970 (only for final benchmark)
Intel Core2Quad 9550

Numbering

Lexicographic Red-Black Minimum Degree

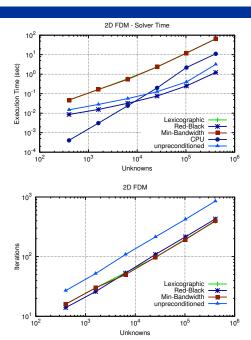
Remarks

Setup purely on CPU, not included Data transfer costs not included OpenCL for both GPUs

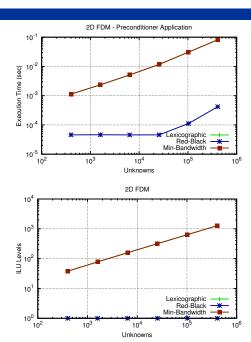
Benchmark

Case Study 1: 2D Poisson, Structured Grid

Benchmarks



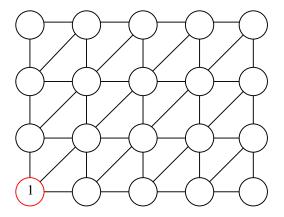
Benchmarks



Coloring

Color dependency graph

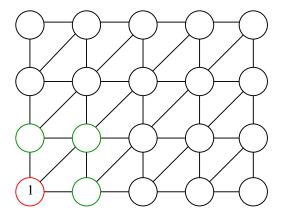
Purely algebraic



Coloring

Color dependency graph

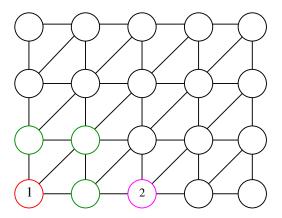
Purely algebraic



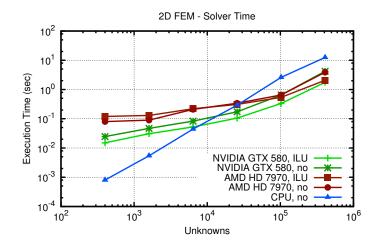
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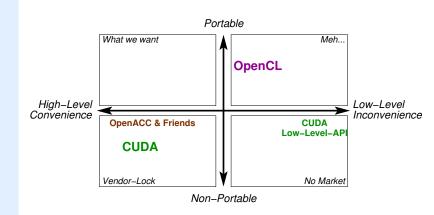
Purely algebraic



Benchmarks



GPU Programming Conclusion



GPU Programming Conclusion

