Highly Productive Application Development with ViennaCL for Accelerators

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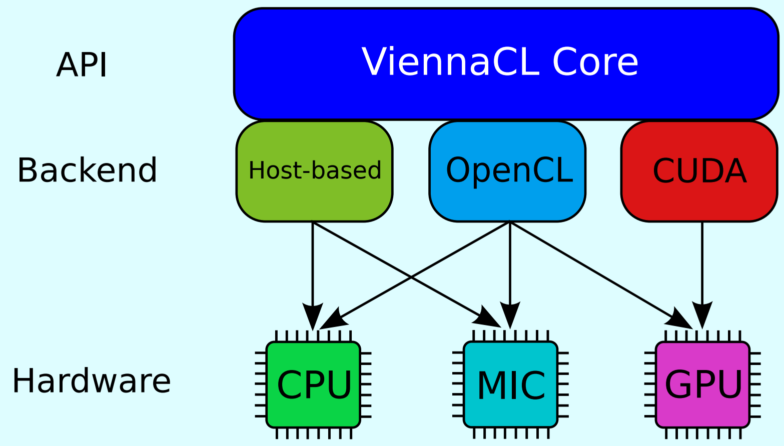
http://viennacl.sourceforge.net/

Motivation

- Common linear algebra operations appear naturally in geophysics.
- Both dense linear algebra and sparse linear algebra operations required.
- Large sparse linear equation systems are solved by iterative methods, which require preconditioners to obtain good convergence rates.
- Novel computing hardware is no longer single-threaded, but requires fine-grained parallelism in order to be used efficiently.
- Various programming models for parallelism: MPI, OpenMP, OpenCL, CUDA, etc.
- Library-centric software development required in order to cope with the increased programming complexity.

About ViennaCL

- Scientific computing library written in C++ (header-only).
- Multiple computing backends: Host-based, OpenCL, and CUDA.
- High-level programming interface, compatible with Boost.uBLAS.
- Focus on iterative solvers: CG, BiCGStab, GMRES.
- Various preconditioners: Jacobi, ICHOL, ILU0, ILUT, AMG, SPAI.
- BLAS level 1, 2, and 3 operations for dense linear algebra.
- MIT (X11) free open-source license.



Code Example

- With Boost.uBLAS: High-level code with syntactic sugar. Single-threaded.

```

using namespace boost::numeric::ublas;

matrix<double> A(1000, 1000);
vector<double> x(1000), y(1000);

/* Fill A, x, y here */

double val = inner_prod(x, y);
y += 2.0 * x;
A += val * outer_prod(x, y);

// Upper triangular solver: Ax = y
x = solve(A, y, upper_tag());

std::cout << "  2-norm: " << norm_2(x) << std::endl;
std::cout << "sup-norm: " << norm_inf(x) << std::endl;
```

- With ViennaCL: Only a change of namespaces required. GPU-accelerated.

```
using namespace viennacl;
using namespace viennacl::linalg;

matrix<double> A(1000, 1000);
vector<double> x(1000), y(1000);

/* Fill A, x, y here */

double val = inner_prod(x, y);
y += 2.0 * x;
A += val * outer_prod(x, y);

// Upper triangular solver: Ax = y
x = solve(A, y, upper_tag());

std::cout << "  2-norm: " << norm_2(x) << std::endl;
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```

Benchmark Results

- Out-of-the-box performance gain of high-level implementation by up to a factor three over LAPACK for QR factorizations.
- Up to 500 GFLOPs for single-precision matrix-matrix-multiplications on NVIDIA GTX 580.
- Up to ten-fold performance gain for iterative solvers.
- Memory-bandwidth is the limiting factor for iterative solvers.

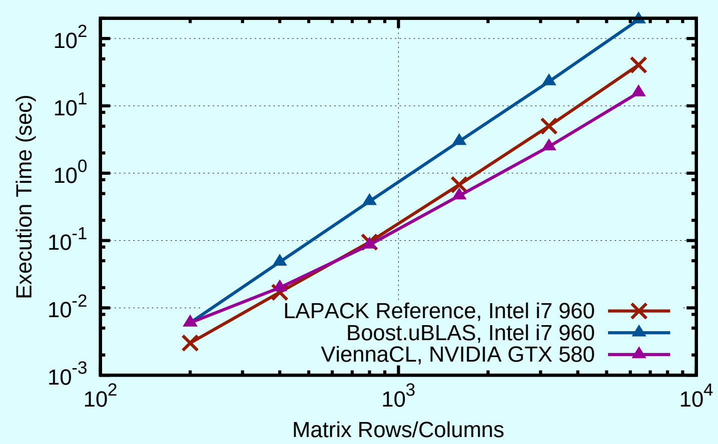

Fig. 1: Comparison of execution times of QR factorizations.

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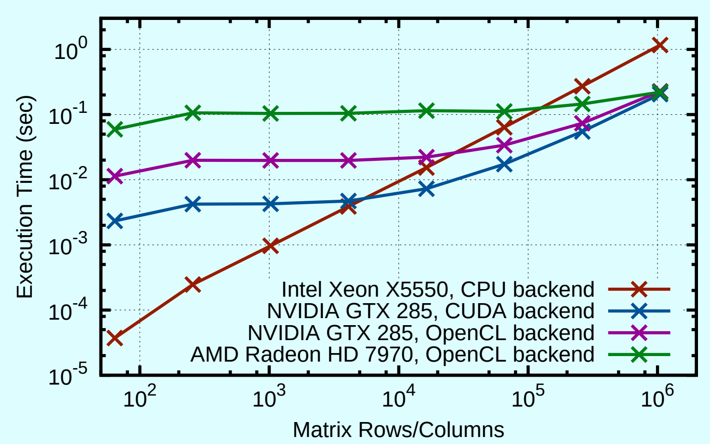

Fig. 2: Comparison of execution times for 50 CG iterations.