# BOAST

## Performance Portability Using Meta-Programming and Auto-Tuning

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**Journées SUCCES, Grenoble**

October 17, 2017

# Scientific Application Portability

## Limited Portability

- Huge codes (more than 100 000 lines), Written in FORTRAN or C++
- Collaborative efforts
- Use many different programming paradigms (OpenMP, OpenCL, CUDA, ...)

## But Based on Computing Kernels

- Well defined parts of a program
- Compute intensive
- Prime target for optimization

## Kernels Should Be Written

- In a portable manner
- In a way that raises developer productivity
- To present good performance

# HPC Architecture Evolution

## Very Rapid and Diverse, Top500:

- Sunway processor (TaihuLight)
- Intel processor + Xeon Phi (Tianhe-2)
- AMD processor + nVidia GPU (Titan)
- IBM BlueGene/Q (Sequoia)
- Fujitsu SPARC64 (K Computer)
- Intel processor + nVidia GPU (Tianhe-1)
- AMD processor (Jaguar)

## Tomorrow?

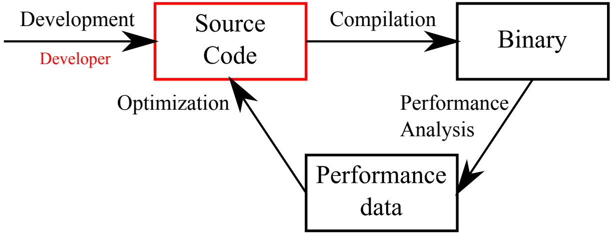
- ARM + DSP?
- Intel Atom + FPGA?
- Quantum computing?

How to write kernels that could adapt to those architectures?
(well maybe not quantum computing...)

# Related Work

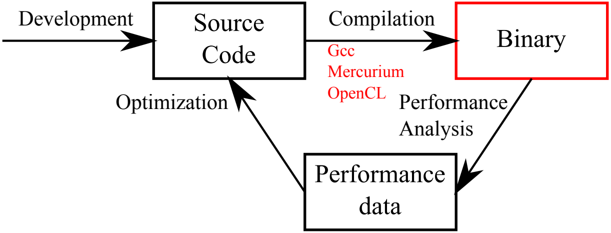
- **Ad hoc autotuners (usually for libraries):**
  - **Atlas** [6] (C macro processing)
  - **SPIRAL** [4] (DSL)
  - ...
- **Generic frameworks using annotation systems:**
  - **POET** [7] (external annotation file)
  - **Orio** [3] (source annotation)
  - **BEAST** [1] (Python preprocessor based, embedded DSL for optimization space definition/pruning)
- **Generic frameworks using embedded DSL:**
  - **Halide** [5] (C++, not very generic, 2D stencil targeted)
  - **Heterogeneous Programming Library** [2] (C++)

# Classical Tuning of Computing Kernels



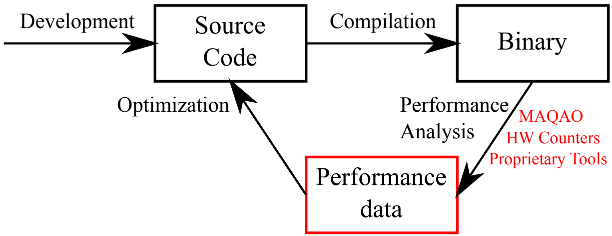

- Kernel optimization workflow
- Usually performed by a knowledgeable developer

# Classical Tuning of Computing Kernels



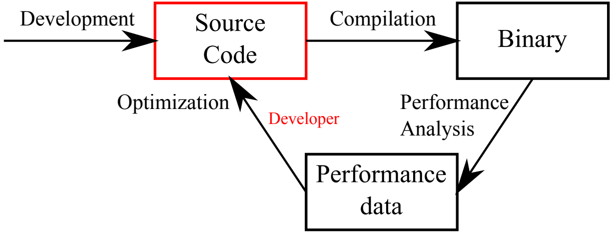

- Compilers perform optimizations
- Architecture specific or generic optimizations

# Classical Tuning of Computing Kernels



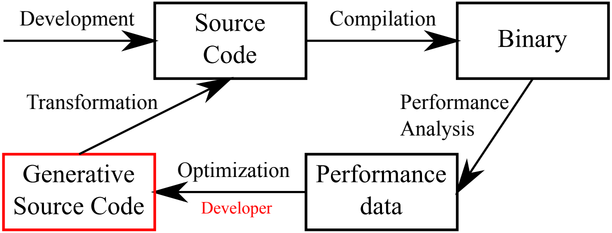

- Performance data hint at source transformations
- Architecture specific or generic hints

# Classical Tuning of Computing Kernels



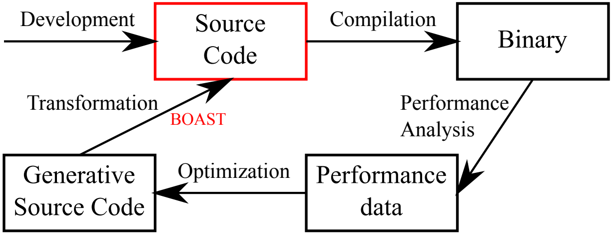

- Multiplication of kernel versions and/or loss of versions
- Difficulty to benchmark versions against each-other

# BOAST Workflow



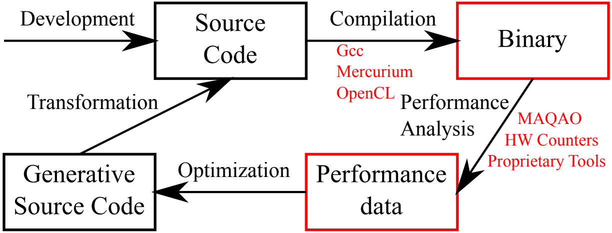

- Meta-programming of optimizations in BOAST
- High level object oriented language

# BOAST Workflow



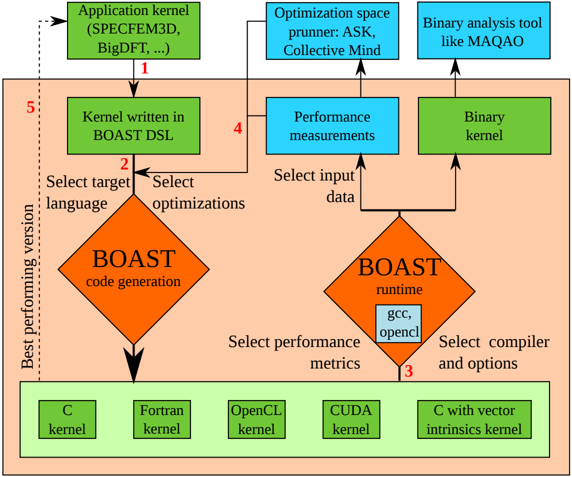

- Generate combination of optimizations
- C, OpenCL, FORTRAN and CUDA are supported

# BOAST Workflow




- Compilation and analysis are automated
- Selection of best version can also be automated

# BOAST Architecture



# Gysela 2d Advection

Gysela: Gyrokinetic Semi-Lagrangian

Tokamak plasma simulation for fusion (ITER)

- Preparation steps
  - Extract 4 targeted routines from Gysela (subpart of 2d advection)
  - Change **API** of the 2d advection kernel
    only arrays of integers and floats for inputs/outputs
    (transmitting data structures is *possible* but more *complex*)
  - Define valid *fake* inputs for the kernel to design a regression test
  - Integrate the reference/original version into BOAST
- Install ruby & BOAST on 4 parallel machines
  - Easiest step
  - Get a working compilation/execution of the kernel: a bit more difficult
- Write a meta-program that *prints* a program
  1. Need to learn a little bit of ruby & BOAST
  2. **Incremental approach: begin with internal routines then external**
  3. Identify what are the *parameters* of the auto-tuning
  4. Integrate the best kernel version to the Gysela compilation process

# Gysela 2d avection (2)

- Auto-tuning parameters that we chose
  - directive based inlining / BOAST driven inlining
  - BOAST driven loop unrolling
  - C or Fortran code generated
  - scan versions of gfortran/gcc/icc/ifort (`module load`)
  - loop blocking parameter (one of the most internal loop)
  - explicit vectorization: BOAST generates INTEL intrinsincs, e.g.

```
ftmp1 = _mm256_setzero_pd( );
ftmp2 = _mm256_setzero_pd( );
ftmp1 = _mm256_fmadd_pd( base1[0], _mm256_load_pd( &ftransp[(0) * (4)]);
ftmp2 = _mm256_fmadd_pd( base1[0 + 1], _mm256_load_pd( &ftransp[(0 + 1) * (4)] ), ftmp2 );
```

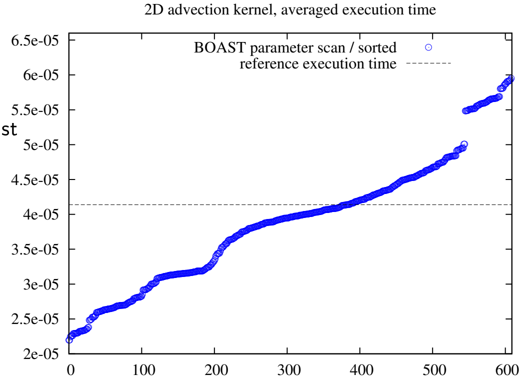
- Final result
  - ruby code of 200 lines for the 2d advection kernel
    compared to original fortran code of 300 lines
- Auto-tuning runs
  - configure the list of modules/compilers for the *parameter scan*
  - between 1 min and 20 min for the parameter scan on 1 machine

# Auto-tuning on INTEL Westmere (2011)

Auto-tuning for 2D advection
Computing center at Marseille
12-cores node -
Intel X5675, 3.07GHz

Nb of runs in this scan: 609
Runs sorted from quickest to slowest
Result of the scan
(best parameters):

```
:lang: FORTRAN
:unroll: true
:force.inline: true
:intrinsic: false
:blocking.size: 4
:module: intel/16.0.2
```




Speedup: 1.9

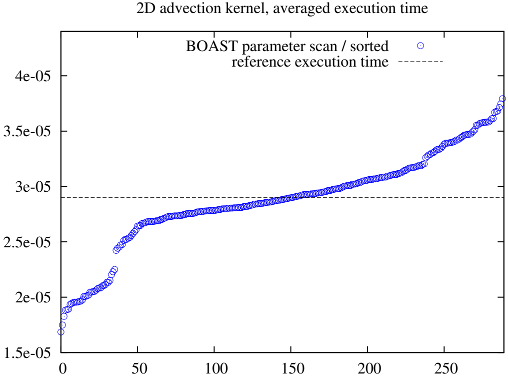
# Auto-tuning on INTEL Sandy-Bridge (2012)

Auto-tuning for 2D advection
Computing center at Orsay
16-cores node -
Intel E5-2670 v1, 2.60GHz

Result of the scan
(best parameters):

```
:lang: FORTRAN
:unroll: false
:force.inline: false
:intrinsic: false
:blocking.size: 2
:module: intel/15.0.0
```

Speedup: 1.7



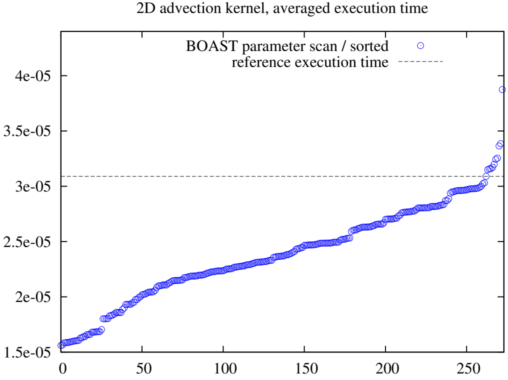
# Auto-tuning on INTEL Haswell (2015)

Auto-tuning for 2D advection
Computing center at Montpellier
24-cores node -
Intel E5-2690 v3, 2.60GHz

Result of the scan
(best parameters):

```
:lang: FORTRAN
:unroll: true
:force.inline: true
:intrinsic: false
:blocking.size: 4
:module: intel/14.0.4.211
```

Speedup: 2.0



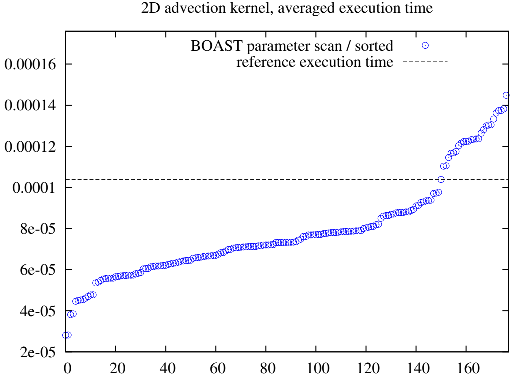
# Auto-tuning on INTEL KNL (Phi 2016)

Auto-tuning for 2D advection
Computing center at Montpellier
64-cores node -
Intel 7210 1.30GHz

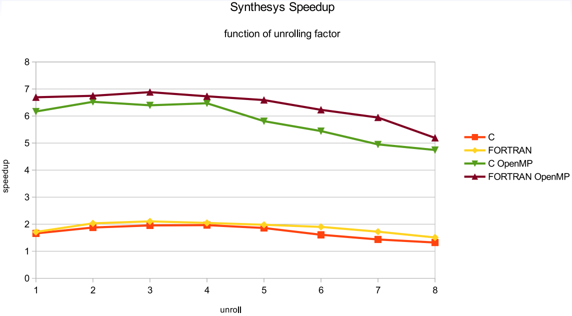
Result of the scan
(best parameters):

```
:lang: FORTRAN
:unroll: true
:force.inline: true
:intrinsic: false
:blocking.size: 32
:module: intel/17.0
```

Speedup: 3.6



# BigDFT




- Novel approach for DFT computation based on Daubechies wavelets
- Fortran and C code, MPI, OpenMP, supports CUDA and OpenCL
- Reference is hand tuned code on target architecture (Nehalem)
- Toward a BLAS-like library for wavelets

# SPECFEM3D

- Seismic wave propagation simulator
- SPECFEM3D ported to OpenCL using BOAST
  - Unified code base (CUDA/OpenCL)
  - Refactoring: kernel code base reduced by 40%
  - Similar performance on NVIDIA Hardware
  - Non regression test for GPU kernels
- On the Mont-Blanc prototype:
  - OpenCL+MPI runs
  - Speedup of 3 for the GPU version

# Conclusions

- BOAST v2.0 is released
- BOAST language features:
  - Unified C and FORTRAN with OpenMP support,
  - Unified OpenCL and CUDA support,
  - Support for vector programming.
- BOAST runtime features:
  - Generation of parametric kernels,
  - Parametric compilation,
  - Non-regression testing of kernels,
  - Benchmarking capabilities (PAPI support)
  - Co-execution and numa-aware capabilities (using hwloc)

# Perspectives

- Ongoing work on other applications: Alya, dgtd_nano3d
- Couple BOAST with other tools:
  - Parametric space pruners (speed up optimization),
  - Binary analysis (guide optimization, MAQAO),
  - Source to source transformation (improve optimization),
  - Binary transformation (improve optimization).
- Improve BOAST:
  - Improve the eDSL to make it more intuitive,
  - Better vector support,
  - Gather feedback.

# And the Future?

New architectures:

- FPGAs:
  - Supported via OpenCL,
  - longer compile time,
  - parallel compilation?
- New vector architectures:
  - Intel KNL and onward: masked vector instructions,
  - ARM SVE: meta programming is in the instruction set.
- New memory architectures:
  - 3D stacked high performance memory (KNL, GPUs): new address space,
  - Non Volatile RAM: new address space again (relevant for computing kernels?)?

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