DEVITO V4.3: PRODUCTION-GRADE MULTI-GPU SUPPORT

Fabio Luporini[1], Rhodri Nelson[2], George Bisbas[2], Italo Assis[4], Ken Hester[3], Gerard Gorman[1,2]

1. *Devito Codes*
2. *Imperial College London*
3. *NVidia*
4. *Federal University of Rio Grande do Norte*

Rice 2021 O&G HPC Conference

Traditional approach to solving PDEs

$$m\frac{\partial^2 u}{\partial t^2} + \eta\frac{\partial u}{\partial t} - \Delta u = 0$$

```
void kernel(…) {
  …
  <impenetrable code with aggressive
performance optimizations>
  …
}
```

Traditional approach to solving PDEs

MATH

↓

CODE

Space = physics × discretization × architecture × language × developers

Huge space ⇒ Huge cost

Raising the level of abstraction

$$m\frac{\partial^2 u}{\partial t^2} + \eta\frac{\partial u}{\partial t} - \Delta u = 0$$

```
void kernel(…) {
  …
  <impenetrable code with aggressive
performance optimizations>
  …
}
```

Raising the level of abstraction

$$m\frac{\partial^2 u}{\partial t^2} + \eta\frac{\partial u}{\partial t} - \Delta u = 0$$

```
void kernel(…) {
  …
  <impenetrable code with aggressive performance optimizations>
  …
}
```

Raising the level of abstraction

$$m\frac{\partial^2 u}{\partial t^2} + \eta\frac{\partial u}{\partial t} - \Delta u = 0$$

Raising the level of abstraction

$$m\frac{\partial^2 u}{\partial t^2} + \eta\frac{\partial u}{\partial t} - \Delta u = 0$$

```
eqn = m * u.dt2 + eta * u.dt - u.laplace
```

Raising the level of abstraction

$$m\frac{\partial^2 u}{\partial t^2} + \eta\frac{\partial u}{\partial t} - \Delta u = 0$$

```
eqn = m * u.dt2 + eta * u.dt - u.laplace
```

```
void kernel(…) { … }
```

Raising the level of abstraction

$$m\frac{\partial^2 u}{\partial t^2} + \eta\frac{\partial u}{\partial t} - \Delta u = 0$$

Devito

```
eqn = m * u.dt2 + eta * u.dt - u.laplace
```

```
void kernel(…) { … }
```

Devito: a DSL and compiler for explicit finite differences

- **Open source platform** – MIT license.

- **Python** package — easy to learn

- **Devito is a compiler** that generates optimized parallel code.
  - Supported languages:
    - {C, SIMD, OpenMP, OpenACC} + MPI
  - Supported architectures:
    - CPUs: Intel, AMD, ARM
    - GPUs: NVidia, AMD

- **Composability: integrate with existing codes and AI/ML**
  - Works out-of-the-box with other popular packages from the Python ecosystem (e.g. PyTorch, NumPy, Dask, TensorFlow)

- **Best practises software engineering** (testing, CI/CD, …)

- **Cloud ready**

Target applications

- **Seismic imaging**
  - FWI, RTM, LS-RTM (TTI, elastic, visco-elastic propagators, etc.)
- Now maturating strong interest in **medical imaging**
- Generation of high performance **neural networks**
- **CFD problems** in renewable energy
- Black-Scholes in **finance**
- Virtually any partial differential equations on structured grids; more generally, any sort of stencil code

Devito on GPUs

- Implementation needs to take into account:
  - Support for multiple target languages
    - OpenMP, OpenACC
    - potentially: CUDA, HIP, SYCL, …
  - Unreliability of the target languages' software stack
  - Multi-GPU support:
    - Make it possible to run different shots on different GPUs
    - Single-node multi-GPU via domain decomposition
    - Multi-node multi-GPU via domain decomposition
  - Data movement
  - Data streaming
  - Kernel performance (e.g., register optimization)

This is already quite hard…

… But much harder is the **automation**!

$$m\frac{\partial^2 u}{\partial t^2} + \eta\frac{\partial u}{\partial t} - \Delta u = 0$$

```
eqn = m * u.dt2 + eta * u.dt - u.laplace
```

The user expresses the mathematical operators; the same exact DSL code needs to run efficiently on different architectures

The key is decomposition

- Compilation is a hard problem
- The key to success is decomposition: a hard problem is decomposed into many — more manageable and simpler — subproblems
- Here the hard problem is the generation of efficient GPU code
- The subproblems are **a series of compilation passes**
- Each compilation pass in isolation doesn't do much. But altogether they solve the problem while ensuring **maintainability** and **extendibility.**

Example: forward propagation with CPU-GPU data streaming

```
m * u.dt2 + eta * u.dt - u.laplace = 0

…

…

…

usave = u

…
```

Example: forward propagation with CPU-GPU data streaming

Compiler pass 1: buffering to decouple CPU-GPU execution

```
m * u.dt2 + eta * u.dt - u.laplace = 0

...

ubuffer = u

...

usave = ubuffer

...
```

Too large for the GPU memory; it will reside on the host

Example: forward propagation with CPU-GPU data streaming

Compiler pass 1: buffering to decouple CPU-GPU execution

```
m * u.dt2 + eta * u.dt - u.laplace = 0
```

GPU
(thread$_0$)

```
…

ubuffer = u
```

```
…
```

CPU
(thread$_1$)

```
usave = ubuffer

…
```

Example: forward propagation with CPU-GPU data streaming

Compiler pass 2: analysis and placement of synchronizations

```
m * u.dt2 + eta * u.dt - u.laplace = 0
```

GPU
(thread$_0$)

```
<wait(lock)>

ubuffer = u
```

```
<on signal>

usave = ubuffer

<unset(lock)>
```

CPU
(thread$_1$)

Example: forward propagation with CPU-GPU data streaming

Compiler pass 3: lowering into Abstract Syntax Trees

GPU
($thread_0$)

```
<loop nest>

while(lock == 0);

<loop nest>
-----------------------------------------------------------------
while(flag != 0)

    <loop nest>

    lock = 2;
```

CPU
($thread_1$)

Example: forward propagation with CPU-GPU data streaming

Compiler pass 4: specialization for the target language

GPU
(thread$_0$)

```
<loop nest>

while(lock == 0);

<loop nest>
```

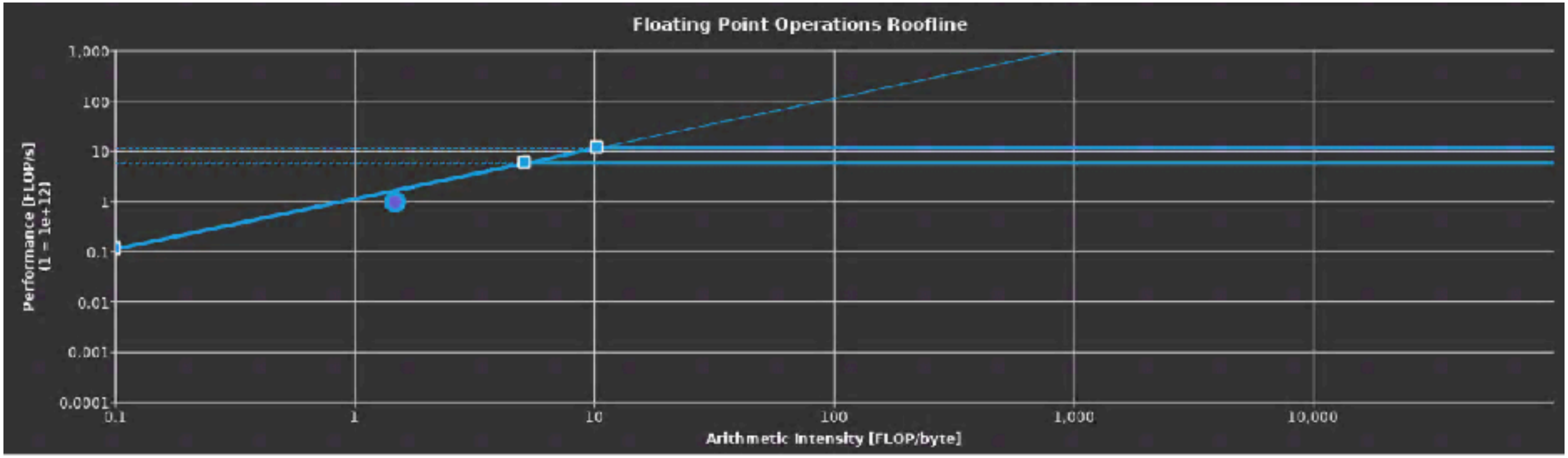
CPU
(thread$_1$)

```
while(flag != 0)

    #pragma acc update self(… ubuffer …)

    lock = 2;
```

Performance of iso-acoustic benchmark



- Achieved performance
  - 27 GPoints/s
  - This corresponds to slightly less than 1 Teraflops/s
  - The measured arithmetic intensity is 1.5. This means ~53% of the attainable peak

- Benchmark details:
  - Benchmark: O(2, 8), 512^3 grid points, 150 timesteps, single precision, NO data streaming
  - System: NVidia V100, nvc 20.9 compiler, NSight Compute for the roofline
  - Optimization: OpenACC, tuned thread block size, all divisions lifted, all arithmetic redundancies eliminated (factorization, time-invariants, etc), constant folding (where reasonable)

- Bottleneck
  - Register pressure => affects occupancy
  - This is an aggressively optimized implementation with OpenACC; we'll probably need to use a lower level language to push it even higher on the roofline

Sponsors who supported this work

- DUG
- BP
- Shell
- Microsoft
- NVidia
- Intel

- Thanks to our many collaborators and contributors. For a full list of contributors for each release please see https://github.com/devitocodes/devito/releases

GPU support roadmap

- Support for multiple target languages
  - OpenMP, OpenACC
  - potentially: CUDA, HIP, SYCL, …
- Unreliability of the target languages' software stack
- Multi-GPU support:
  - Make it possible to run different shots on different GPUs
  - Single-node multi-GPU via domain decomposition
  - Multi-node multi-GPU via domain decomposition
- Data movement (optimized)
- Data streaming (optimized)
- Kernel performance (best so far: 27 GPOINTS on iso-acoustic O(2, 8))

Legend:

Done

Nearly done

In progress

Potentially later this year