

Devito

Automated fast finite difference computation

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Finite Difference Methods

$$f'(a) \approx \frac{f(a+h) - f(a)}{h} \quad (1)$$

- Taylor series expansion
- Calculate derivatives of any order with relative simplicity
- Mathematically simple method for solving PDEs

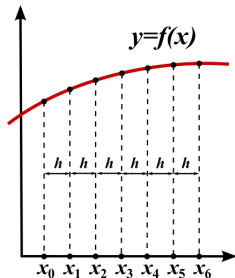


Figure: Discretizing a function on a grid (Wikipedia)

Why FD?

The acoustic wave equation

$$\frac{\partial^2 u}{\partial x^2} - \frac{1}{c^2} \frac{\partial^2 u}{\partial t^2} = 0 \quad (2)$$

Discretized:

$$u_i^{n+1} = -u_i^{n-1} + 2u_i^n + C^2(u_{i+1}^n - 2u_i^n + u_{i-1}^n) \quad (3)$$

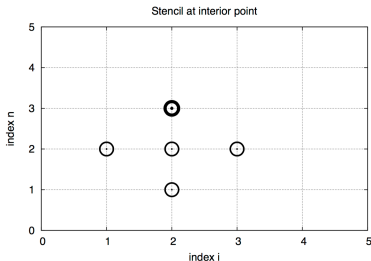


Figure: Mesh in space and time for a 1D wave equation

Why the wave equation?

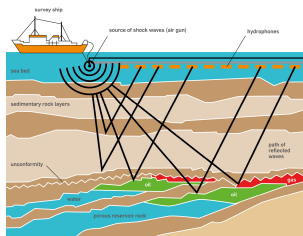


Figure: Offshore seismic survey

Seismic imaging

- RTM
 - Inputs: Velocity Model, Seismic Data
 - Output: Seismic image
- FWI
 - Inputs: Initial Velocity Model, Seismic Data
 - Output: Improved Velocity Model

Pure Python Implementation

```
for ti in range(0, nt):
    for a in range(1, nx-1):
        for b in range(1, ny-1):
            if ti == 0:
                u[ti, a, b] = self.ts(0, 0, 0, 0, 0, 0,
                                     m[a, b], dt, h, damp[a, b])
            elif ti == 1:
                u[ti, a, b] = self.ts(0, u[ti - 1, a - 1, b],
                                     u[ti - 1, a, b],
                                     u[ti - 1, a + 1, b],
                                     u[ti - 1, a, b - 1],
                                     u[ti - 1, a, b + 1],
                                     m[a, b], dt, h, damp[a, b])
            else:
                u[ti, a, b] = self.ts(u[ti - 2, a, b],
                                     u[ti - 1, a - 1, b],
                                     u[ti - 1, a, b],
                                     u[ti - 1, a + 1, b],
                                     u[ti - 1, a, b - 1],
                                     u[ti - 1, a, b + 1],
                                     m[a, b], dt, h, damp[a, b])
```

Why does it need to be fast?

- Large number of operations: ≈ 5000 FLOPs per loop iteration of a 16th order TTI Kernel
- Realistic problems have large grids: $1580 \times 1580 \times 1130 \approx 2.82$ Billion points (SEAM Benchmark)
- $2.82 \times 10^9 \times 5000 \times 3000(t) \times 2$ (forward-reverse) $\approx 8.5 \times 10^{16}$ per iteration of FWI
- Typically ≈ 30000 FWI iterations ($\approx 2.5 \times 10^{21} = 2.5 \times 10^9$ TFLOPs)

≈ 135 wall-clock hours on the TACC Stampede (ideally)

Why automated

Computer Science

- Fast code is complex
 - Loop blocking
 - OpenMP clauses
 - Vectorisation - intrinsics
 - Memory - alignment, NUMA
 - Factorization
 - FMA
- Fast code is platform dependent
 - Intrinsics
 - CUDA
 - OpenCL
- Fast code is error prone

Geophysics

- Change of discretizations
- Change of physics
 - Anisotropy - VTI/TTI
 - Elastic equation
- Boundary conditions
- Continuous acquisition

SymPy - Symbolic computation in Python

- Symbolic computer algebra system written in pure Python
- Features
 - Complex symbolic expressions as Python object trees
 - Symbolic manipulation routines and interfaces
 - Convert symbolic expressions to numeric functions
 - Python or NumPy functions
 - C or Fortran kernels

For specialised domains generating C code is not enough!

Devito - a prototype Finite Difference DSL

Devito - A Finite Difference DSL for seismic imaging

- Aimed at creating fast high-order inversion kernels
- Development is driven by "real world" problems

Based on SymPy expressions

- The acoustic wave equation:

$$m \frac{\partial^2 u}{\partial t^2} + \eta \frac{\partial u}{\partial t} - \nabla u = 0 \quad (4)$$

can be written as

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

Devito auto-generates optimised C kernel code

- OpenMP threading and vectorisation pragmas
- Cache blocking and auto-tuning
- Symbolic stencil optimisation (eg. CSE, hoisting)

Devito

Devito Data Objects
TimeData('u', shape=())
DenseData('m', shape=())

Act as symbols in expression
 +
 numpy arrays

Stencil Equation
 $eqn = m * u.dt2 - u.laplace$

Expands to symbolic kernel (finite-difference)

User Input

Devito Operator
Operator(eqn)

Transforms stencil in indexed format

Devito Propagator

Autogenerates C code

Devito Compiler
 GCC — Clang — Intel — Intel® Xeon Phi™

Compiles and loads platform
 specific executable function

Figure: An overview of Devito's architecture

Devito

Real-world applications need more than PDE solvers

- File I/O and support for large datasets
- Non PDE kernel code e.g. sparse point interpolation
- Ability to easily interface with complex outer code

Devito follows the principle of graceful degradation

- Circumvent restrictions to the high-level API by customisation
- Devito translates high-level PDE-based stencils into "matrix index" format in steps

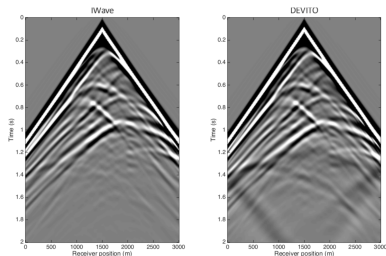
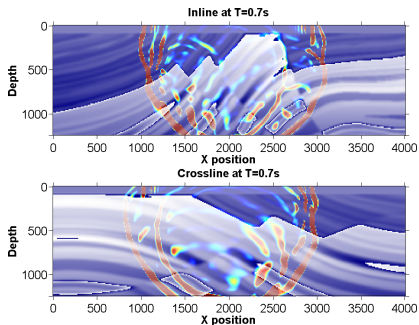
```
# High-level expression equivalent to f.dx2
(-2*f(x, y) + f(x - h, y) + f(x + h, y)) / h**2
# Low-level expression with explicit indexing
(-2*f[x, y] + f[x - 1, y] + f[x + 1, y]) / h**2
```

- Allows custom functionality in auto-generated kernels

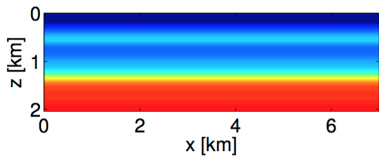
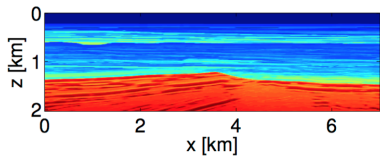
Seismic Imaging

Full waveform inversion

- Acoustic and TTI wave equations of varying spatial order
- Numerically verified against Industrial standard software on standard datasets
- Achieved performance is also comparable to industrial standard software



FWI



Example code for forward propagation

```
def forward(model, nt, dt, h, order=2):
    shape = model.shape
    m = DenseData(name="m", shape=shape,
                  space_order=order)
    m.data[:] = model
    u = TimeData(name="u", shape=shape,
                 time_dim=nt, time_order=2,
                 space_order=order, save=True)
    eta = DenseData(name="eta", shape=shape,
                    space_order=order)
    # Derive stencil from symbolic equation
    eqn = m * u.dt2 - u.laplace + eta * u.dt
    stencil = solve(eqn, u.forward)[0]
    op = Operator(stencils=Eq(u.forward, stencil),
                  nt=nt, subs={s: dt, h: h}, shape=shape,
                  forward=True)
    # Source injection code omitted for brevity
    op.apply()
```

```

// #include directives omitted for brevity
extern "C" int ForwardOperator(double *u_vec, double *damp_vec, double *m_vec, double *src_vec, double *rec_vec)
{
    double (*u)[130][130][130] = (double (*)[130][130][130]) u_vec;
    double (*damp)[130][130] = (double (*)[130][130]) damp_vec;
    double (*m)[130][130] = (double (*)[130][130]) m_vec;
    double (*src)[1] = (double (*)[1]) src_vec;
    float (*src_coords)[3] = (float (*)[3]) src_coords_vec;
    double (*rec)[101] = (double (*)[101]) rec_vec;
    float (*rec_coords)[3] = (float (*)[3]) rec_coords_vec;
    {
        #pragma omp parallel
        for (int i4 = 0; i4 < 149; i4 += 1)
        {
            {
                #pragma omp for schedule(static)
                for (int i1b = 1; i1b < 129 - (128 % i1block); i1b += i1block)
                    for (int i2b = 1; i2b < 129 - (128 % i2block); i2b += i2block)
                        for (int i1 = i1b; i1 < i1b + i1block; i1++)
                            for (int i2 = i2b; i2 < i2b + i2block; i2++)
                                {
                                    #pragma omp simd aligned(damp, m, u:64)
                                    for (int i3 = 1; i3 < 129; i3++)
                                        {
                                            double temp1 = damp[i1][i2][i3];
                                            double temp2 = m[i1][i2][i3];
                                            double temp4 = u[i4 - 1][i1][i2][i3];
                                            double temp5 = u[i4 - 2][i1][i2][i3];
                                            u[i4][i1][i2][i3] = ...
                                        }
                                }
                            }
                }
            }
        }
    }
    for (int i1 = 129 - (128 % i1block); i1 < 129; i1++)
        for (int i2 = 1; i2 < 129 - (128 % i2block); i2++)
            {

```

```
def adjoint(model, nt, dt, h, spc_order=2):
    m = DenseData("m", model.shape)
    m.data[:] = model
    v = TimeData(name='v', shape=model.shape, time_dim=nt,
                 time_order=2, space_order=spc_order,
                 save=False)
    damp = DenseData("damp", model.shape)

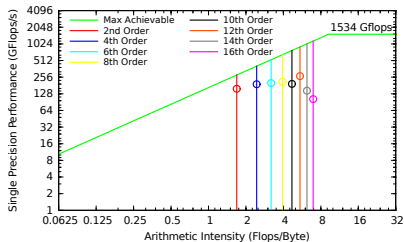
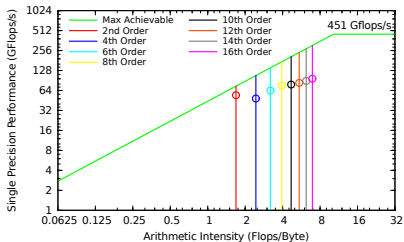
    # Derive stencil from symbolic equation
    eqn = m * v.dt2 - v.laplace - damp * v.dt
    stencil = solve(eqn, v.backward)[0]

    # Add spacing substitutions
    subs = {s: dt, h: h}
    op = Operator(stencils=Eq(u.backward, stencil), nt=nt,
                 shape=model.shape, subs=subs, forward=False)
    op.apply()
```

Performance

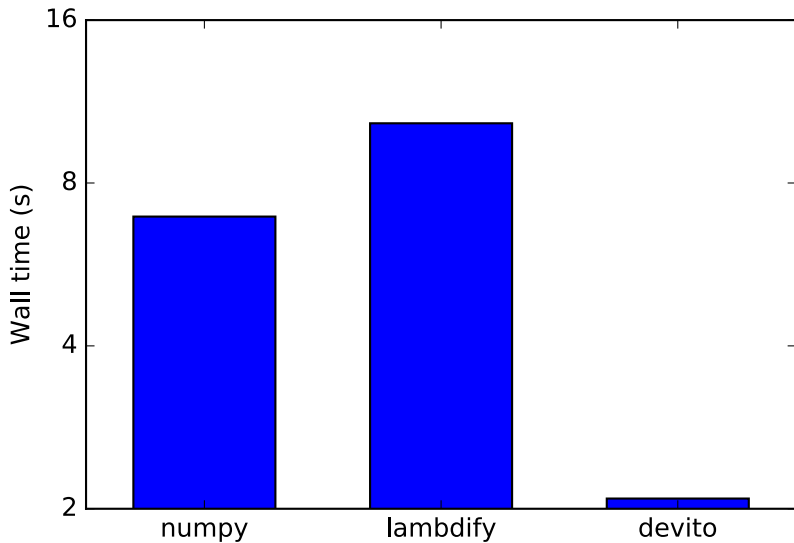
Performance of acoustic forward operator

- Intel Xeon E5-2690v2 10C 3GHz and a Intel[®] Xeon Phi[™] Knights Corner
- Model size 201 x 201 x 70 + 40 ABC
- Grid size 15m 10Hz Ricker wavelet source



Performance

2D Diffusion equation on a single core



Performance Optimizations

Automated code optimizations:

- OpenMP and vectorization pragmas
- Loop blocking and auto-tuning for block size
- Automated roofline plotting for performance analysis

Symbolic Optimizations

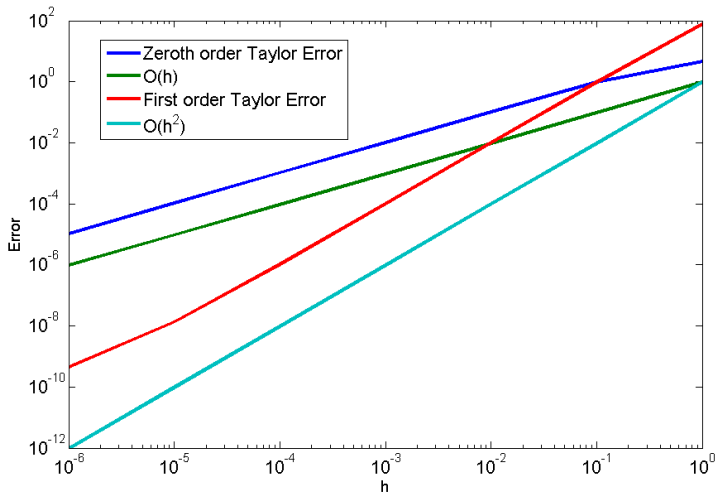
- Common Subexpression elimination
 - Reduces compilation time from hours to seconds for large stencils
 - Enables further factorization techniques to reduce flops

Potential future optimizations

- Polyhedral compilation (time blocking)
- Automated data layout optimizations

Verification

Adjoint Test and Gradient Test



Conclusions

- Devito: A finite difference DSL for seismic imaging
 - Symbolic problem description (PDEs) via SymPy
 - Low-level API for kernel customisation
 - Automated performance optimisation
- Devito is driven by real-world scientific problems
 - Not yet another stencil compiler
 - Bridge the gap between stencil compilers and real world applications
- Future work:
 - Extend feature range to facilitate more science
 - MPI parallelism for larger models
 - Integrate stencil or polyhedral compiler backends
 - Additional symbolic optimisation (factorisation, hoisting, etc.)
 - Integrate automated verification tools to catch compiler bugs

Thank you

Publications

- N. Kukreja, M. Louboutin, F. Vieira, F. Luporini, M. Lange, and G. Gorman. Devito: automated fast finite difference computation. Accepted for WOLFHPC16, to appear in ACM SIGHPC, 2016
- M. Lange, N. Kukreja, M. Louboutin, F. Luporini, F. Vieira, V. Pandolfo, P. Velesko, P. Kazakas, and G. Gorman. Devito: Towards a generic Finite Difference DSL using Symbolic Python. Accepted for PyHPC2016, to appear in ACM SIGHPC, 2016
- M. Louboutin, M. Lange, N. Kukreja, F. Herrmann, and G. Gorman. Performance prediction of finite-difference solvers for different computer architectures. Submitted to Computers and Geosciences, 2016

