

Devito: Symbolic Math for Automated Fast Finite Difference Computations

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Introduction

Devito

Example

Finite Difference



The 1D acoustic wave equation

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

Discretized:

$$u_i^{n+1} = -u_i^{n-1} + 2u_i^n + \frac{c^2 dt^2}{h^2} (u_{i+1}^n - 2u_i^n + u_{i-1}^n)$$
 (2)

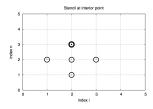


Figure 1: Mesh in space and time for a 1D wave equation

- Mathematically simple method for solving PDEs directly
- Calculate derivatives of any order with relative simplicity
- Easier to optimize performance than FEM codes

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Pure Python Implementation



```
k = (c*dt/h)**2
for t in range(2,nsteps-1):
    p[xs,zs,t] = s[t]
    for z in range(1,nz-1):
        for x in range(1,nx-1):
            p[x,z,t] += 2*p[x,z,t-1] - p[x,z,t-2] + k*(p[x+1,z,t-1]-4*p[x,z,t-1]+p[x-1,z,t-1]+p[x,z+1,t-1]+p[x,z-1,t-1])
```

Why does it need to be fast?



- \bullet Large number of operations: ≈ 6000 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 ¹)
- $2.82 \times 10^9 \times 6000 \times 3000(t) \times 2$ (forward-reverse) $\approx 10^{17}$ FLOPs per shot
- Typically ≈ 30000 shots ($\approx 3\times 10^{21} = 3\times 10^9$ TFLOPs per FWI iteration)
- Typically \approx 15 FWI iterations (\approx 4.6 \times 10 22 = 46 billion TFLOPs total)

 ≈ 100 wall-clock days executing on the TACC Stampede (assuming linpack-level performance)

Why automated



Computer science

- Fast code is complex
 - Loop blocking
 - OpenMP clauses
 - Vectorization intrinsics
 - Memory alignment, NUMA
 - Common sub-expression elimination
 - ADD/MUL balance
 - Denormal numbers
 - Elemental functions
 - Non temporal stores
- Fast code is platform dependent
 - Intrinsics
 - CUDA/OpenCL
 - Data layouts
- Fast code is error prone

Geophysics

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

Introduction

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Example

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 specialized 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:

$$m\frac{\partial^2 u}{\partial t^2} + \eta \frac{\partial u}{\partial t} - \nabla u = 0$$
 (3)

can be written as

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

Devito auto-generates optimized C kernel code

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 customization
- Allows custom functionality in auto-generated kernels

Devito Symbolic Engine (DSE)



- Symbolic manipulations to reduce the number of required flops
- Common subexpression elimination enables further optimizations and improves compilation time
- Heuristic refactorization 0.3 * a + + 0.3 * b => 0.3 * (a + b)
- Approximations Replace transient functions (e.g. trigonometric) with polynomial approximations
- Heuristic hoisting of time-invariants

Devito Loop Engine (DLE)



- Optimizations for parallelism and memory
- SIMD
- OpenMP including collapse
- Loop blocking (only in spatial dimensions)
- Loop fission + elemental functions
- Non-temporal stores
- Padding + data alignment

Devito Architecture



sympy. Equation

SymbolicData

- sympy.Function
- Data allocation

Dimension

- Iteration space
- Function index

Iteration

- Expression - SymPy expr traversal
- Symbolic properties (dims, vars, etc.)
- Substitution
- C code generation

- Loop instance
- Loop limits (variable vs. fixed)
- Vectorisation
- OpenMP pragmas
- Substitution
- C code generation

Operator

- Universal entry-point: convert SymPy expressions
- Manage codegen, compilation and execution
- Manage cross expression data (eg. temporaries)
- Configurable by users (eg. DSE, blocking, etc.)
- Composable/mergeable

Devito Symbolic Engine

Devito Loop Engine

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Introduction

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Example

Example - 2D diffusion equation

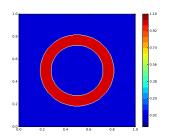


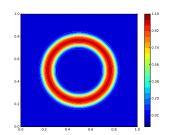
To illustrate let's consider the 2D diffusion equation:

$$\frac{\partial u}{\partial t} = \alpha \nabla^2 u = \alpha \left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$

Example: Smoothing a sharp-edged ring

• Finite difference with 5-point stencil





Example - 2D diffusion equation



We can solve this using Python (slow) ...

```
for ti in range(timesteps):
    t0 = ti % 2
    t1 = (ti + 1) % 2
    for i in range(1, nx-1):
        for j in range(1, ny-1):
            uxx = (u[t0,i+1,j] - 2*u[t0,i,j] + u[t0,i-1,j]) / dx2
            uyy = (u[t0,i,j+1] - 2*u[t0,i,j] + u[t0,i,j-1]) / dy2
            u[t1,i,j] = u[t0,i,j] + dt * a * (uxx + uyy)
```

Vectorized NumPy (faster) ...

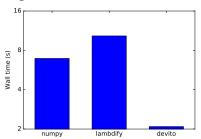
```
for ti in range(timesteps):
    t0 = ti % 2
    t1 = (ti + 1) % 2
# Vectorised version of the diffusion stencil
    uxx = (u[t0,2:,1:-1]-2*u[t0,1:-1,1:-1]+u[t0,:-2,1:-1])/dx2
    uyy = (u[t0,1:-1,2:]-2*u[t0,1:-1,1:-1]+u[t0,1:-1,:-2])/dy2
    u[t1,1:-1,1:-1] = u[t0,1:-1,1:-1] + a * dt * (uxx + uyy)
```

Example - 2D diffusion equation



Solve symbolically in Devito:

Single core benchmark:



Typical loop nest - Devito code



```
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_order=2,
                 space_order=order)
   eta = DenseData(name='eta', shape=shape,
                    space order=order)
   # Derive stencil from symbolic equation
   eqn = m * u.dt2 - u.laplace + eta * u.dt
    stencil = [Eq(u.forward, solve(eqn, u.forward)[0])]
   # Add source and receiver interpolation
    source = u.inject(src * dt^2 / m)
   receiver = rec.interpolate(u)
   # Create and execute operator kernel
   op = Operator(stencils=source + stencil + receiver,
                  subs={s: dt. h: h})
   op.apply(t=nt)
```

Generated Code

#pragma omp parallel

_MM_SET_DENORMALS_ZERO_MODE(_MM_DENORMALS_ZERO_ON);
MM SET FLUSH ZERO MODE(MM FLUSH ZERO ON):



```
#pragma omp parallel
  for (int i4 = 0; i4 < 329; i4 + = 1)
   struct timeval start main, end main;
   #pragma omp master
    gettimeofday(&start_main, NULL);
     #pragma omp for schedule(static)
     for (int i1 = 8: i1<122: i1++)
       for (int i2 = 8: i2<122: i2++)
          #pragma omp simd aligned(damp, m, u:64)
          for (int i3 = 8: i3<122: i3++)
           u[i4][i1][i2][i3] = ((3.04F*damp[i1][i2][i3] - 2*m[i1][i2][i3])*u[i4 - 2][i1][i2][
                  i31 - 1.12198912198912e - 7F*(n[i4 - 1][i1][i2][i3 - 8] + n[i4 - 1][i1][i2][i3]
                  + 8] + u[i4 - 1][i1][i2 - 8][i3] + u[i4 - 1][i1][i2 + 8][i3] + u[i4 - 1][i1
                   - 81[i2][i3] + u[i4 - 1][i1 + 8][i2][i3]) + 2.34472828758543e-6F*(u[i4 -
                  1][i1][i2][i3 - 7] + u[i4 - 1][i1][i2][i3 + 7] + u[i4 - 1][i1][i2 - 7][i3] +
                   u[i4 - 1][i1][i2 + 7][i3] + u[i4 - 1][i1 - 7][i2][i3] + u[i4 - 1][i1 + 7][
                  i21[i31] - 2.39357679357679e-5F*(u[i4 - 1][i1][i2][i3 - 6] + u[i4 - 1][i1][
                  11[i1 - 6][i2][i3] + n[i4 - 1][i1 + 6][i2][i3]) + 1.60848360528361e-4F*(n[i2][i3])
                  i4 - 11[i11[i21[i3 - 5] + n[i4 - 11[i11][i21[i3 + 5] + n[i4 - 11[i11][i2 - 5][
                  i3] + u[i4 - 1][i1][i2 + 5][i3] + u[i4 - 1][i1 - 5][i2][i3] + u[i4 - 1][i1 +
                   5][i2][i3]] - 8.16808080808081e-4F*(u[i4 - 1][i1][i2][i3 - 4] + u[i4 - 1][
                  i1][i2][i3 + 4] + u[i4 - 1][i1][i2 - 4][i3] + u[i4 - 1][i1][i2 + 4][i3] + u[
                  i4 - 1][i1 - 4][i2][i3] + u[i4 - 1][i1 + 4][i2][i3]) + 3.48504781144781e-3F
                  *(n[i4 - 1][i1][i2][i3 - 3] + n[i4 - 1][i1][i2][i3 + 3] + n[i4 - 1][i1][i2 -
                   31[i3] + n[i4 - 1][i1][i2 + 3][i3] + n[i4 - 1][i1 - 3][i2][i3] + n[i4 - 1][i3]
                  i1 + 3[i2][i3] - 1.4375822222222e-2F*(u[i4 - 1][i1][i2][i3 - 2] + <math>u[i4 - 1][i4]
                  1][i1][i2][i3 + 2] + u[i4 - 1][i1][i2 - 2][i3] + u[i4 - 1][i1][i2 + 2][i3] +
                  u[i4 - 1][i1 - 2][i2][i3] + u[i4 - 1][i1 + 2][i2][i3]) + 8.2147555555555566
                  -2F*(u[i4 - 1][i1][i2][i3 - 1] + u[i4 - 1][i1][i2][i3 + 1] + u[i4 - 1][i1]
                  i2 - 1][i3] + u[i4 - 1][i1][i2 + 1][i3] + u[i4 - 1][i1 - 1][i2][i3] + u[i4
                   1][i1 + 1][i2][i3]) + 4*m[i1][i2][i3]*u[i4 - 1][i1][i2]
                  4.23474709115646e-1F*u[i4 - 1][i1][i2][i3])/(3.04E**
                 1[i2][i3]):
                                                                             London
```

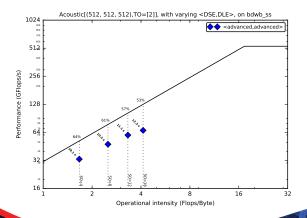
Generated Code



```
#pragma omp master
   gettimeofday(&end_main, NULL);
   timings->main += (double)(end main.tv sec-start main.tv sec)+(double)(end main.tv usec-
          start main.tv usec)/1000000:
 #pragma omp single
   struct timeval start_post_stencils0, end_post_stencils0;
   gettimeofday(&start_post_stencils0, NULL);
   for (int p_src = 0; p_src < 1; p_src += 1)
      u[i4][(int)(floor(5.0e-2F*src coords[p src][0])) + 40][(int)(floor(5.0e-2F*src coords[
            p_src[1]) + 40][(int)(floor(5.0e-2F*src_coords[p_src][2])) + 40] = 9.2416F
            *(-1.25e-4F*(float)(-2.0e+1F*(int)(floor(5.0e-2F*src coords[p src][0])) +
            src coords[p src][0])*(float)(-2.0e+1F*(int)(floor(5.0e-2F*src coords[p src][1])
            ) + src coords[p src][1])*(float)(-2.0e+1F*(int)(floor(5.0e-2F*src coords[p src
            [2])) + src coords[p src][2]) + 2.5e-3F*(float)(-2.0e+1F*(int)(floor(5.0e-2F*
            src coords[p src][0]) + src coords[p src][0])*(float)(-2.0e+1F*(int)(floor(5.0e
            -2F*src coords[p src][1]) + src coords[p src][1]) + 2.5e-3F*(float)(-2.0e+1F*(
            int)(floor(5.0e-2F*src coords[p src][0])) + src coords[p src][0])*(float)(-2.0e
            +1F*(int)(floor(5.0e-2F*src_coords[p_src][2])) + src_coords[p_src][2]) - 5.0e-2F
            *(float)(-2.0e+1F*(int)(floor(5.0e-2F*src coords[p src][0])) + src coords[p src
            [0] + 2.5e-3F*(float)(-2.0e+1F*(int)(floor(5.0e-2F*src coords[p src][1])) +
            src_coords[p_src][1])*(float)(-2.0e+1F*(int)(floor(5.0e-2F*src_coords[p_src][2])
            ) + src coords[p src][2]) - 5.0e-2F*(float)(-2.0e+1F*(int)(floor(5.0e-2F*
            src coords[p src][1])) + src coords[p src][1]) - 5.0e-2F*(float)(-2.0e+1F*(int)(
            floor(5.0e-2F*src_coords[p_src][2])) + src_coords[p_src][2]) + 1)*src[i4][p_src
            ]/m[(int)(floor(5.0e-2F*src coords[p src][0])) + 40][(int)(floor(5.0e-2F*src coords[p src][0]))
            src coords[p src][1])) + 40][(int)(floor(5.0e-2F*src coords[p src][2])) + 40] +
            u[i4][(int)(floor(5.0e-2F*src_coords[p_src][0])) + 40][(int)(floor(5.0e-2F*
            src coords[p src][1])) + 40][(int)(floor(5.0e-2F*src coords[p src][2])) + 40];
      u[i4][(int)(floor(5.0e-2F*src coords[p src][0])) + 40][(int)(floor(5.0e-2F*src coords
             [p\_src][1]) + 41][(int)(floor(5.0e-2F*src\_coords[p\_src][2])) + 40] = 9.2416F
             *(1,25e-4F*(float)(-2,0e+1F*(int)(floor(5,0e-2F*src coords[p src][0])) +
             src_coords[p_src][0])*(float)(-2.0e+1F*(int)(floor(5.0e-2F*src_coords[p_src
             l[1])) + src coords[p src][1])*(float)(-2.0e+1F*(int)(floor(5.0e-2F*src coords[
             p_src][2])) + src_coords[p_src][2]) - 2.5e-3F*(float)(-2.0e+1F*( mp)(floor(5.0e)
             -2F*src_coords[p_src][0])) + src_coords[p_src][0])*
                                                                             3F+ (010 10) 12.0e
             (5.0e-2F*src_coords[p_src][1])) + src_coords[p_src]
             +1F*(int)(floor(5.0e-2F*src coords[p sred
```

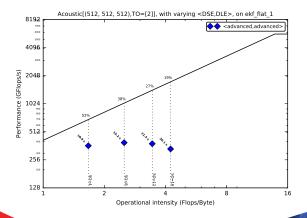


- Performance of acoustic forward operator
- Intel®Xeon™E5-2620 v4 2.1Ghz Broadwell (8 cores per socket, single socket)
- Model size $512 \times 512 \times 512$, $t_n = 250$



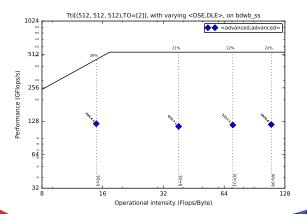


- Performance of acoustic forward operator
- Intel[®]Xeon Phi[™]7650 Knightslanding (68 cores) Quadrant Mode
- Model size $512 \times 512 \times 512$, $t_n = 3000$



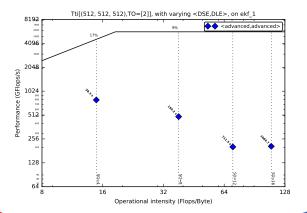


- Performance of TTI forward operator
- Intel®Xeon™E5-2620 v4 2.1Ghz Broadwell (8 cores per socket, single socket)
- Model size $512 \times 512 \times 512$, $t_n = 250$





- Performance of TTI forward operator
- Intel[®]Xeon Phi[™]7650 Knightslanding (68 cores) Quadrant mode
- Model size $512 \times 512 \times 512$, $t_n = 3000$



Conclusions



- Devito: A finite difference DSL for seismic imaging
 - Symbolic problem description (PDEs) via SymPy
 - Low-level API for kernel customization
 - Automated performance optimization
- · Devito is driven by real-world scientific problems
 - Bring the latest in performance optimization closer to real science
- Future work:
 - Extend feature range to facilitate more science
 - MPI parallelism for larger models
 - Integrate stencil or polyhedral compiler backends like YASK
 - Integrate automated verification tools to catch compiler bugs ¹

¹Christopher Lidbury, Andrei Lascu, Nathan Chong, and Alastair F Donaldson. Many-core compiler fuzzing. In ACM SIGPLAN Notices volume 50, pages 65–76. ACM, 2015

Thank you



Publications

- N. Kukreja, M. Louboutin, F. Vieira, F. Luporini, M. Lange, and G. Gorman. Devito: automated fast finite difference computation. WOLFHPC 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. PyHPC 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

Poster

- Wednesday, March 1 4:30 PM 6:30 PM
- Minisymposterium: Software Productivity and Sustainability for CSE and Data Science (Galleria)











