StreamJIT: A Commensal Compiler for High-Performance Stream Programming

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Modern software is built out of libraries

There’s a C, Java and/or Python library for basically every domain.

<table>
<thead>
<tr>
<th>Library</th>
<th>Category</th>
<th>Language</th>
</tr>
</thead>
<tbody>
<tr>
<td>ImageMagick</td>
<td>image processing</td>
<td>C</td>
</tr>
<tr>
<td>LAPACK/BLAS</td>
<td>linear algebra</td>
<td>C</td>
</tr>
<tr>
<td>CGAL</td>
<td>computational geometry</td>
<td>C++</td>
</tr>
<tr>
<td>EJML</td>
<td>linear algebra</td>
<td>Java</td>
</tr>
<tr>
<td>Weka</td>
<td>data mining</td>
<td>Java</td>
</tr>
<tr>
<td>Pillow</td>
<td>image processing</td>
<td>Python</td>
</tr>
<tr>
<td>NLTK</td>
<td>natural language processing</td>
<td>Python</td>
</tr>
</tbody>
</table>

If a library doesn’t exist for our domain, we build one, then build our application on top of it.
Domain-specific languages are better

Domain-specific languages can exploit domain knowledge in ways general-purpose languages can’t, providing

- clean abstractions
- domain-specific semantic checks
- domain-specific optimizations

Despite these benefits, domain-specific languages are rare.
The high-performance DSL recipe

- lexer, parser, type-checker/inference
- domain-specific semantic checks
- general-purpose optimizations (e.g., inlining, common subexpression elimination)
- domain-specific optimizations
- optimization heuristics and machine performance models
- code generation (C, JVM bytecode, LLVM IR)
- debugging, profiling and IDE support
- interface with other languages, or enough general-purpose features to do without
The high-performance DSL recipe: actual value

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Embedded DSLs get us to here.
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Commensal compilers reduce effort to just the domain knowledge.
Commensal compilation

Commensal compilers implement domain-specific languages on top of managed language runtimes.\(^1\)

Massive investment in optimizing JIT compilers.

Let the JIT compiler do the heavy lifting. Only do the missing domain-specific optimizations.

I’ll talk about the JVM, but .NET provides similar features.

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\(^1\)In ecology, a commensal relationship between species benefits one species without affecting the other; e.g., barnacles on a whale.
I’ll talk about two commensal compilers today.

- a matrix math compiler built around the EJML library, which has two APIs, a simple API and a high performance API; our compiler lets users code to the simple API without forgoing performance (not in the paper)
- StreamJIT, a stream programming language strongly inspired by StreamIt, which provides 2.8 times better average throughput than StreamIt with an order-of-magnitude smaller compiler
Simple API or high performance?

\[ y = z - Hx \quad \Rightarrow \quad y = z.\text{minus}(H.\text{mult}(x)); \]

\[ S = HPH^T + R \quad \Rightarrow \quad S = H.\text{mult}(P).\text{mult}( \]
\[ \quad \quad \quad H.\text{transpose()}.\text{plus}(R); \]

\[ K = PH^T S^{-1} \quad \Rightarrow \quad P.\text{mult}(H.\text{transpose()}.\text{mult(} \]
\[ \quad \quad \quad S.\text{invert()})); \]

\[ x = x + Ky \quad \Rightarrow \quad x = x.\text{plus}(K.\text{mult}(y)); \]

\[ P = P - KHP \quad \Rightarrow \quad P = P.\text{minus}(K.\text{mult}(H).\text{mult}(P)); \]
Simple API or high performance?

\[ y = z - Hx \]
\[ S = HPH^T + R \]
\[ K = PHTS^{-1} \]
\[ x = x + Ky \]
\[ P = P - KHP \]

Domain knowledge is temporary matrix reuse, transposed multiplies, and destructive operations. Operations API is 19% faster.
Commensal EJML compiler user interface

The user codes against the simple API, then calls our compiler to get an object implementing the same interface and uses it as normal.

```java
KalmanFilter f = new Compiler().compile(KalmanFilter.class,
    KalmanFilterSimple.class,
    F, Q, H, new DenseMatrix64F(9, 1), new DenseMatrix64F(9, 9));

/* use f as normal */
DenseMatrix64F R = CommonOps.identity(measDOF);
for (DenseMatrix64F z : measurements) {
    f.predict();
    f.update(z, R);
}
```
Commensal EJML compiler passes

We’ll compile the simple API to the complex one by

1. building an expression DAG from the compiled bytecode
2. fusing multiply and transpose
3. packing temporaries, using inplace operations when possible
4. building a method handle chain that calls the complex API

Users get both the simple API and good performance.
Building the expression DAG

String name = ci.getMethod().getName();
if (name.equals("getMatrix") || name.equals("wrap"))
    exprs.put(i, exprs.get(fieldMap.get(ci.getArgument(0))));
else if (name.equals("invert"))
    exprs.put(i, new Invert(exprs.get(ci.getArgument(0))));
else if (name.equals("transpose"))
    exprs.put(i, new Transpose(exprs.get(ci.getArgument(0))));
else if (name.equals("plus"))
    exprs.put(i, new Plus(
        exprs.get(ci.getArgument(0)),
        exprs.get(ci.getArgument(1))));
else if (name.equals("minus"))
    exprs.put(i, new Minus(
        exprs.get(ci.getArgument(0)),
        exprs.get(ci.getArgument(1))));
else if (name.equals("mult"))
    exprs.put(i, Multiply.regular(
        exprs.get(ci.getArgument(0)),
        exprs.get(ci.getArgument(1))));

58 lines to build expression DAG from SSA-style bytecode IR.
private static void foldMultiplyTranspose(Expr e) {
    if (e instanceof Multiply) {
        Multiply m = (Multiply)e;
        Expr left = m.deps().get(0), right = m.deps().get(1);
        if (left instanceof Transpose) {
            m.deps().set(0, left.deps().get(0));
            m.toggleTransposeLeft();
        }
        if (right instanceof Transpose) {
            m.deps().set(1, right.deps().get(0));
            m.toggleTransposeRight();
        }
    }
    e.deps().forEach(Compiler::foldMultiplyTranspose);
}
We want to generate code that reuses the JVM’s full optimizations.

- Interpret the expression DAG
  - dynamism inhibits JVM optimization
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- Emit bytecode
  - complicated; moves compiler one metalevel up

We can use method handles to easily generate optimizable code.
Method handles

Method handles are typed, partially-applicable function pointers.

static final method handles are constants, so are their bound arguments – so the JVM can inline method handle chains all the way through.

```java
private static final MethodHandle UPDATE = ...;
public void update(DenseMatrix64F z, DenseMatrix64F R) {
    UPDATE.invokeExact(z, R);
}
```
public static MethodHandle apply(MethodHandle f, MethodHandle... args){
    for (MethodHandle a : args)
        f = MethodHandles.collectArguments(target, 0, a);
    return f;
}

private static void _semicolon(MethodHandle... handles) {
    for (MethodHandle h : handles)
        h.invokeExact();
}

private static final MethodHandle SEMICOLON = findStatic(Combinators.class, "_semicolon");

public static MethodHandle semicolon(MethodHandle... handles) {
    return SEMICOLON.bindTo(handles);
}
public static MethodHandle apply(MethodHandle f, MethodHandle... args){
    for (MethodHandle a : args)
        f = MethodHandles.collectArguments(target, 0, a);
    return f;
}

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}
Commensal EJML code generation

We walk the expression DAG, asking each node to provide a method handle.

```java
final MethodHandle ADD = findStatic(CommonOps.class, "add", params(3)),
    ADD_EQUALS = findStatic(CommonOps.class, "addEquals", params(2));

public MethodHandle operate(List<MethodHandle> sources, MethodHandle sink) {
    if (sources.get(0) == sink)
        return Combinators.apply(ADD_EQUALS, sources.get(0), sources.get(1));
    else if (sources.get(1) == sink)
        return Combinators.apply(ADD_EQUALS, sources.get(1), sources.get(0));
    return Combinators.apply(ADD, sources.get(0), sources.get(1), sink);
}
```
Inlining all the way down

```java
private static final MethodHandle UPDATE = ...;
public void update(DenseMatrix64F z, DenseMatrix64F R) {
    UPDATE.invokeExact(z, R);
}

UPDATE is a constant, so the JVM inlines it.
```
Inlining all the way down

```java
public void update(DenseMatrix64F z, DenseMatrix64F R) {
    this.z = z;
    this.R = R;
    for (MethodHandle h : HANDLES)
        h.invokeExact();
}

The HANDLES array is a constant, so the JVM can unroll the loop.
```
Inlining all the way down

```java
public void update(DenseMatrix64F z, DenseMatrix64F R) {
    this.z = z;
    this.R = R;
    HANDLES[0].invokeExact();
    HANDLES[1].invokeExact();
    HANDLES[2].invokeExact();
    HANDLES[3].invokeExact();
    HANDLES[4].invokeExact();
    HANDLES[5].invokeExact();
    HANDLES[6].invokeExact();
    HANDLES[7].invokeExact();
    HANDLES[8].invokeExact();
    HANDLES[9].invokeExact();
    HANDLES[10].invokeExact();
    HANDLES[11].invokeExact();
    HANDLES[12].invokeExact();
}
```

The JVM can inline each array element method handle.
public void update(DenseMatrix64F z, DenseMatrix64F R) {
    this.z = z;
    this.R = R;
    mult(MH, MH, MH);
    multTransB(MH, MH, MH);
    addEquals(MH, MH);
    invert(MH);
    multTransA(MH, MH, MH);
    mult(MH, MH, MH);
    mult(MH, MH, MH);
    mult(MH, MH, MH);
    subEquals(MH, MH);
    mult(MH, MH, MH);
    sub(MH, MH, MH);
    mult(MH, MH, MH);
    addEquals(MH, MH);
}

The argument-providing handles \texttt{MH} are constants, so the JVM can inline them.
Inlining all the way down

```java
public void update(DenseMatrix64F z, DenseMatrix64F R) {
    this.z = z;
    this.R = R;
    mult(this.H, this.P, t1);
    multTransB(t, this.H, t2);
    addEquals(t2, this.R);
    invert(t2);
    multTransA(this.H, t2, t1);
    mult(this.P, t1, t3);
    mult(t3, this.H, t2);
    mult(t2, this.P, t4);
    subEquals(this.P, t4);
    mult(this.H, this.x, t5);
    sub(this.z, t5, t5);
    mult(t3, t5, t1);
    addEquals(this.x, t1);
}
```

The JVM can continue to optimize just as with hand-written code.
730 non-comment lines of code; about a week of effort.

EJML Kalman filter benchmark:
Simple API: 1793ms
Complex API: 1503ms
Commensal-compiled simple API: 1529ms
StreamJIT

StreamIt is a synchronous dataflow stream programming language. The StreamIt compiler emits C code for GCC.

The StreamIt compiler is 266,000 lines of Java, including a 31,000-line Eclipse IDE plugin.

The StreamJIT commensal compiler is 27,000 lines of Java and Python – an order of magnitude smaller than StreamIt and smaller than StreamIt’s IDE plugin alone.

StreamJIT achieves 2.8 times better throughput than StreamIt on StreamIt’s own benchmark suite.
Synchronous dataflow programs are graphs of (mostly) stateless workers with statically-known data rates.

Using the data rates, the compiler can compute a schedule of worker executions, fuse workers and introduce buffers to remove synchronization, then choose a combination of data, task and pipeline parallelism to fit the machine.
StreamJIT Workflow

User worker classes

Code to build graph

Surrounding application code

javac

.class files

Other app code

StreamJIT library

StreamJIT compiler

method handle chain

JVM JIT

compile time

run time

autotuner
Fusion, data-parallel fission and splitter/joiner removal

IR is domain-level; mirrors stream graph, not worker bodies.
Problems with optimization heuristics

Optimizations themselves are easy. Hard part is deciding when to apply them based on the program, backend compiler, and machine.

We want to reuse the JVM as a black box, not model it.

Modeling hardware kills (performance) portability.

Models require maintenance as the JVM and hardware change.
We delegate our optimization decisions to the OpenTuner extensible autotuner, which decides

- an overall schedule multiplier (to amortize synchronization)
- whether to fuse workers
- whether to remove splitters and joiners
- how to allocate fused groups to cores
Work allocation produces a schedule of worker executions per core.

We build a method handle chain that realizes a loop nest using custom combinators.

```java
private static void _filterLoop(MethodHandle work, int iterations,
                                int subiterations, int pop, int push, int firstIteration) {
    for (int i = firstIteration*subiterations;
         i < (firstIteration+iterations)*subiterations;
         ++i)
        work.invokeExact(i * pop, i * push);
}
```
### Evaluation

<table>
<thead>
<tr>
<th>benchmark</th>
<th>StreamJIT</th>
<th>Streamlt</th>
<th>relative perf</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFT</td>
<td>25,210,084</td>
<td>2,459,016</td>
<td>10.3</td>
</tr>
<tr>
<td>TDE-PP</td>
<td>12,605,042</td>
<td>2,357,564</td>
<td>5.3</td>
</tr>
<tr>
<td>DCT</td>
<td>23,622,047</td>
<td>6,434,316</td>
<td>3.7</td>
</tr>
<tr>
<td>DES</td>
<td>17,441,860</td>
<td>6,469,003</td>
<td>2.7</td>
</tr>
<tr>
<td>Beamformer</td>
<td>2,320,186</td>
<td>1,204,215</td>
<td>1.9</td>
</tr>
<tr>
<td>BitonicSort</td>
<td>9,771,987</td>
<td>6,451,613</td>
<td>1.5</td>
</tr>
<tr>
<td>FMRadio</td>
<td>2,272,727</td>
<td>2,085,143</td>
<td>1.1</td>
</tr>
<tr>
<td>ChannelVocoder</td>
<td>551,065</td>
<td>796,548</td>
<td>0.7</td>
</tr>
<tr>
<td>Filterbank</td>
<td>924,499</td>
<td>1,785,714</td>
<td>0.5</td>
</tr>
<tr>
<td>Serpent</td>
<td>2,548,853</td>
<td>6,332,454</td>
<td>0.4</td>
</tr>
<tr>
<td>MPEG2</td>
<td>32,258,065</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Vocoder</td>
<td>406,394</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

2.8 times higher throughput (outputs/second) on 24 cores.
Commensal compilers reduce the cost of building domain-specific languages by reusing general-purpose languages and runtimes.

Thinking of adding a complex, abstraction-breaking, high-performance API to your library? Build a commensal compiler instead!

https://github.com/jbosboom/commensal-ejml
https://github.com/jbosboom/streamjit
Backup slides
## StreamJIT source breakdown

<table>
<thead>
<tr>
<th>Component</th>
<th>Lines of Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>User API (plus private interpreter plumbing)</td>
<td>1,213</td>
</tr>
<tr>
<td>Interpreter</td>
<td>1,032</td>
</tr>
<tr>
<td>Compiler</td>
<td>5,437</td>
</tr>
<tr>
<td>Distributed runtime</td>
<td>5,713</td>
</tr>
<tr>
<td>Tuner integration</td>
<td>713</td>
</tr>
<tr>
<td>Compiler/interp/distributed common</td>
<td>4,222</td>
</tr>
<tr>
<td>Bytecode-to-SSA library</td>
<td>5,166</td>
</tr>
<tr>
<td>Utilities (JSON, ILP solver bindings etc.)</td>
<td>2,536</td>
</tr>
<tr>
<td>Total (non-test)</td>
<td>26,132</td>
</tr>
<tr>
<td>Benchmarks and tests</td>
<td>7,880</td>
</tr>
<tr>
<td>Total</td>
<td>33,912</td>
</tr>
</tbody>
</table>
Vectorization limitations

```java
float[] autocorr = new float[this.winsize];
for (int i = 0; i < this.winsize; i++) {
    float sum = 0;
    for (int j = i; j < winsize; j++)
        sum += peek(i) * peek(j);
    autocorr[i] = sum / winsize;
}
```