A Case For Interactive Optimization Assistants

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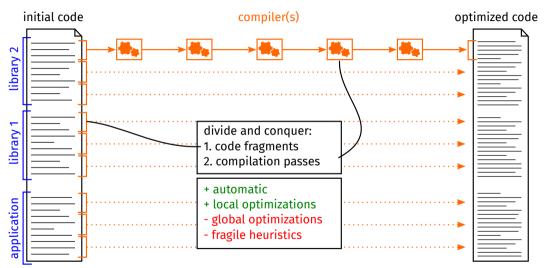


User-Schedulable Languages Workshop @ ASPLOS - March 2025, Rotterdam

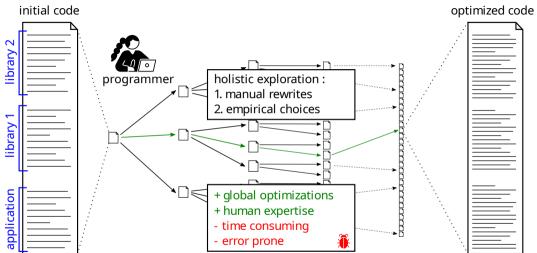
How do we Optimize Programs?



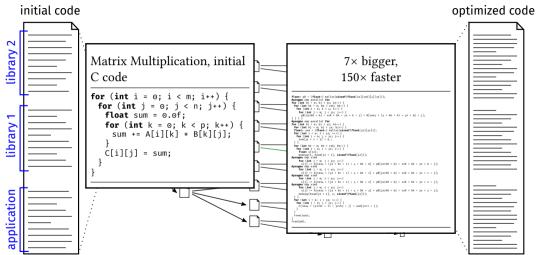
Automatic Compilation Passes



Manual Program Rewriting



Manual Program Rewriting

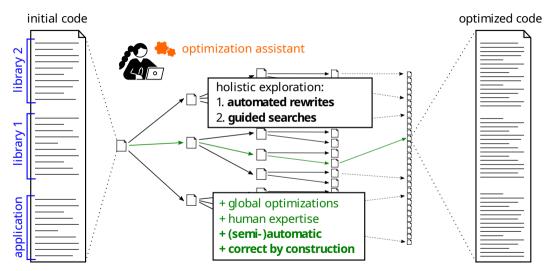


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We Need User-Scheduling

- compilers answer neither current nor future optimization needs
- ▶ algorithms and hardware architectures evolve faster than compilers
- ► falling back to manual optimization **slows down progress**

We Need Interactive Program Rewriting



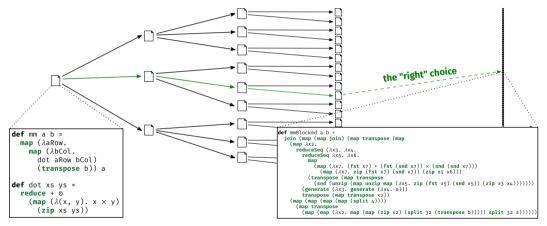
My journey towards interactive optimization assistants:

PhD: Functional Program Rewriting

rewrite rules

(map f). (map g) = map (f . g)

combinatorial rewriting space, correct and extensible



Achieving Expert Optimizations by Composition

6 expert optimizations

 \rightarrow decomposed into **74 rules**

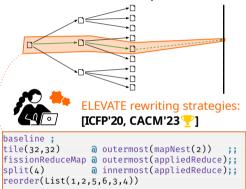
Harris: corner and edge detection



16x faster than OpenCV, 1.4x faster than Halide! [CGO'21]

(4-core ARM Cortex A7)

enormous rewrite space, 10x bigger programs than before, **thousands of rewrite steps**



Extensibility, composability and control matter.

- ► 6 expert optimizations = 51 generic + 19 backend + 4 specific rules
- ▶ can add rules without heavy compiler re-engineering
- ▶ can define custom optimization strategies through higher-order composition

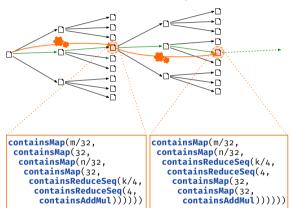
Premature control is the root of all evil.

- strategies took a lot of effort to write
 - ► Harris: 63 strategies, 600 lines of code
 - ► Matmul: 36 strategies, 200 lines of code
- ▶ user responsible for chaining and debugging thousands of rewrite steps
- ▶ strategies were often over-detailed and program-specific
- difficulties scaling to a more diverse and complex benchmark suite

Combining Automatic Search and Human Expertise

Guided Equality Saturation [POPL'24]

automatic rewrite search, sharing equivalent subterms + specifying guides as program sketches guided search : 582x faster, 116x less memory



Sketches Required for TVM-like Matrix Multiplication

1. split "loops"

```
containsMap(m/32,
    containsMap(32,
    containsMap(n/32,
    containsMap(32,
    containsReduceSeq(k/4,
        containsReduceSeq(4,4,
        containsAddMul))))))
```

3. introduce memory

```
containsMap(m / 32,
    containsMap(n / 32,
    containsMap(32,
        containsMap(32,
        containsMap(32,
        containsMap(32,
        containsAddMul))))),
containsToMem(n.k.f32,
    containsMap(n / 32,
    containsMap(32.f32, ?)))))
```

2. reorder "loops"

```
containsMap(m/32,
    containsMap(n/32,
    containsReduceSeq(k/4,
    containsMap(32,
        containsMap(32,
        containsMap(32,
        containsAddMul)))))))
```

4. thread, vectorize, unroll

```
containsMapPar(m / 32,
    containsMap(n / 32,
    containsReduceSeq(k / 4,
    containsMap(32,
        containsMap(1,
        containsAdMulVec)))))),
containsToMem(n.k.f32,
    containsMapPar(n / 32,
    containsMap(1.<32>f32, ?)))))
```

Semi-automation enables parsimonious control.

- simple sketches instead of complex strategies
- ▶ sketches 10× smaller than complete program, focus on key optimization insights
- ▶ sufficient for guided search to infer the rewrites and missing program details

Parsimonious control is not enough for productivity.

- users are not supported in iteratively developing their sketch sequences
- little feedback to help decision-making
- need to learn an unfamiliar language to write sketches
- also relevant to developing rewriting strategies

PostDoc: Assisting Interactive Optimization

OptiTrust Optimization Assistant

What to compute: C code

How to optimize: OCaml script

```
Function.inline_def [cFunDef "mm"];
let tile (id, tile_size) = Loop.tile (int tile_size)
-index:("b" ^ id) -bound:TileDivides [cFor id] in
List.iter tile [("i", 32); ("j", 32); ("k", 4)];
Loop.reorder_at
-order:["bi"; "bj"; "bk"; "i"; "k"; "j"] [cPlusEq ()];
Loop.hoist_expr -dest:[tBefore; cFor "bi"] "pB"
-indep:["bi"; "i"] [cArrayRead "B"];
Matrix.stack_copy -var:"sum -copy_var:"s"
-copy_dims:1 [cFor -body:[cPlusEq ()] "k"];
Omp.parallel_for [cFunBody "mm1024"; cStrict; cFor ""];
Loop.unroll [cFor -body:[cPlusEq ()] "k"];
```

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What to compute: C code

```
void mm(float* C. float* A. float* B.
       int m. int n. int p) {
 reads("A ~> Matrix2(m, p)");
 __reads("B ~> Matrix2(p, n)");
 _modifies("C ~> Matrix2(m, n)");
 for (int i = 0: i < m; i++) {</pre>
   xmodifies("for j in 0..n \rightarrow \delta C[i][j] \rightarrow Cell")
   for (int i = 0: i < n: i++) {
    __xmodifies("&C[i][j] ~> Cell");
    float sum = 0.0f:
    for (int k = 0: k < p: k++)
      sum += A[i][k] * B[k][i]:
    C[i][i] = sum:
```

How to optimize: OCaml script

```
Function.inline_def [cFunDef "mm"];
let tile (id, tile_size) = Loop.tile (int tile_size)
-index:("b" ^ id) -bound:TileDivides [cFor id] in
List.iter tile [("i", 32); ("j", 32); ("k", 4)];
Loop.reorder_at
-order:["bi"; "bj"; "bk"; "i"; "k"; "j"] [cPlusEq ()];
Loop.hoist_expr -dest:[tBefore; cFor "bi"] "pB"
-indep:["bi"; "i] [cArrayRead "B"];
Matrix.stack_copy -var:"sum -copy_var:"s"
-copy_dims:1 [cFor -body:[cPlusEq ()] "k"];
Omp.simd [cFor -body:[cPlusEq ()] "j"];
Omp.arallel_for [cFunBody "mm1024"; cStrict; cFor ""];
Loop.unroll [cFor -body:[cPlusEq ()] "k"];
```

 validated through static resource analysis based on separation logic

Visualizing the Effect of Transformations

Pressing "F6" on a transformation step opens the corresponding diff:

```
for (int i = 0; i < 1024; i++) {
  for (int j = 0; j < 1024; j++) {
    float sum = 0.f;
    for (int k = 0; k < 1024; k++) {
      sum += A[i][k] * B[k][j];
    }
      C[i][j] = sum;
  }
  C[i][j] = sum;
}
</pre>
```

Trace for matmul_check ✓	00 -1,20 +1,38 00				
Preprocessing loop contracts	1 #include <optitrust.h></optitrust.h>	1	<pre>#include <optitrust.h></optitrust.h></pre>		
▶ Function.inline_def [cFunDef "mm"]; ✓	2	2			
▶ List.iter tile [("i", 32); ("j", 32); ("k", 4)]; ✓	<pre>3 void mm1024(float* C, float* A, float* B) {</pre>		<pre>void mm1024(float* C, float* A, float* B) {</pre>		
Loop.reorder_at ~order:["bi"; "bj"; "bk"; "i"; "k"; "j"]	4 for (int bi = 0; bi < 32; bi++) {	4	<pre>for (int bi = 0; bi < 32; bi++) { for (int i = 0; i = 32; i = 1) { </pre>		
[cPlusEq ~lhs:[cVar "sum"] ()]; ✓	5 for (int $i = 0$; $i < 32$; $i + +$) {	6			
✓ Loop.reorder_at ✓	6 for (int bj = 0 ; bj < 32; bj++) {	7			
✓ bring down j ✓	o = 101 (200 b) = 0, b + 0.0 b, 0.0 c, 0.0 c	8			
▶ Loop.hoist_alloc_loop_list ✓		9			
► Loop.fission ✓	7 for (int $j = 0; j < 32; j++$) {	10	<pre>for (int j = 0; j < 32; j++) {</pre>		
► Loop.fission ✓	8 float sum = $0.f$;	11	<pre>sum[MINDEX2(32, 32, i, j)] = 0.f;</pre>		
► Loop_swap.swap ✓		12	}		
✓ bring down j ✓	a fine (det blo a) blo i 200 bloch (13			
Loop.hoist_alloc_loop_list ✓	9 for (int $bk = 0$; $bk < 256$; $bk++$) {	14	<pre>for (int bk = 0; bk < 256; bk++) { for (int i = 0; i < 32; i++) {</pre>		
► Loop.fission ✓		16			
Loop.fission ✓		17			
▶ Loop_swap.swap ✓	10 for (int $k = 0$; $k < 4$; $k++$) {	18			
✓ bring down i ✓		19			
 Loop.hoist_alloc_loop_list ✓ 		20			
	11 sum += A[MINDEX2(1024, 1024, bi * 32 + i, bk * 4 + k)] *	21			
► Loop.fission ✓	<pre>12 B[MINDEX2(1024, 1024, bk * 4 + k, bj * 32 + j)];</pre>	22			
► Loop_swap.swap ✓	13 }	23			
- bring down i d	14 } 15 CIMINDEX2(1024, 1024, bi * 32 + i, bi * 32 + i)] = sum:	24	}		
Loop.hoist_alloc_loop_list ✓	15 C[MINDEX2(1024, 1024, bi * 32 + i, bj * 32 + j)] = sum; 16 }	25	3		
► Loop.fission ✓	10 } 17 }	25			
► Loop.fission ✓		27	for (int $i = 0$; $i < 32$; $i++$) {		
► Loop swap.swap ✓		28			
Loop.hoist_expr ~dest:[tBefore; cFor "bi"] "pB"		29			
~indep:["bi"; "i"] [cArrayRead "B"]; <		30			
Matrix.stack copy ~var:"sum" ~copy var:"s"		31			
~copy_dims:1 [cFor ~body:[cPlusEq ~lhs:[cVar		32			
"sum"] ()] "k"]; 🖌		33			
Omp.simd [nbMulti; cFor ~body:[cPlusEg ~lhs:		34 35			
[cVar "s"] ()] "j"]; ✓	18 }	35			
 Omp.parallel_for [nbMulti; cFunBody ""; cStrict; 	10 } 19 }	30			
	20 }	38			
		•	, ,		
advanced arguments justification					
normal full	full Otde before Code after Decode Hide res Res annot Res context Res usage Full res Compact				

Accessibility, interactivity and feedback matter.

- ▶ familiar C code rather than specialized language / IR
- interactive visualization of intermediate steps (diffs, traces)
 - reversible encoding from C to internal imperative λ -calculus
- no black box code generation: "what you see is what you get"
- reasonably concise scripts thanks to composability
 - ▶ Matmul: 8 script steps result in 55 basic transformations (+61 "ghost transformations").
 - ▶ names are very useful: eases composition as well as targeting and marking subterms.
 - easier to define abstract loop transformations on C

Much remains to be done.

- only subset of C supported
- interactivity and feedback remains basic
- ► no search automation
- ▶ ...

A Case for Interactive Optimization Assistants

1. Extensibility, composability and control matter.

▶ yet, Premature control is the root of all evil.

2. Semi-automation enables parsimonious control.

▶ yet, Parsimonious control is not enough for productivity.

3. Accessibility, interactivity and feedback matter.

• yet, Much remains to be done.

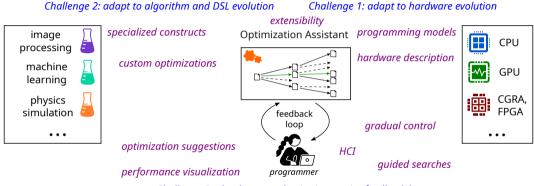
Optimization Assistants: Towards Mainstream User-Scheduling

Mainstream Development Tools:

- Debuggers
- Profilers
- AI Assistants (GitHub Copilot)
- **Optimization Assistants?** (aka. User-Scheduling++)
- ▶ Proof Assistants?

Improve the traditional (profile; manual rewrite; debug) cycle.

A Few Technical Challenges



Challenge 3: develop a productive interactive feedback loop

A Few Community Challenges

The user-scheduling community could benefit from sharing:

- 1. benchmarks
- 2. evaluation methodologies
- 3. software
- 4. terminology definitions?

A Few Community Challenges

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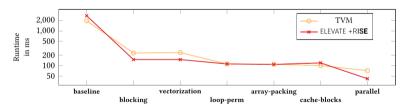
- 1. benchmarks
- 2. evaluation methodologies
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- 4. terminology definitions?

Thanks! I am curious to see where this workshop leads us. (thok.eu

Backup Slides

1st Benchmark: Matrix Multiplication on Intel CPU

- 6 optimizations
 - transform loops blocking, permutation, unrolling
 - change data layout array packing
 - add parallelism vectorization, multi-threading
- performance is on par with reference schedules from TVM.



https://tvm.apache.org/docs/how_to/optimize_operators/opt_gemm.html

2nd Benchmark: Corner Detection on ARM CPUs



- ▶ standard corner detection pipeline
- ▶ 6 well-known optimizations

circular buffering, operator fusion, multi-threading, vectorization, convolution separation, register rotation



extensibility + control

faster code than Halide, with 2 additional optimizations

OptiTrust Matrix Multiplication Performance

- ► Intel(R) Core(TM) i7-8665U CPU, AVX2 (8 floats), 4 cores (8 hyperthreads)
- Relative speedup on 1024³ input:

version	single-thread	multi-thread
unoptimized	$1 \times$	1×
optimized	46 imes	150×
TVM	$46 \times$	$150 \times$
numpy (Intel MKL) ¹	71×	183×

Both codes have 90th percentile runtime of 9.4ms over 200 benchmark runs, corresponding to a speedup of $150 \times$ compared to the 90th percentile of the naive code.

¹uses assembly code, explicit vectorization, custom thread library