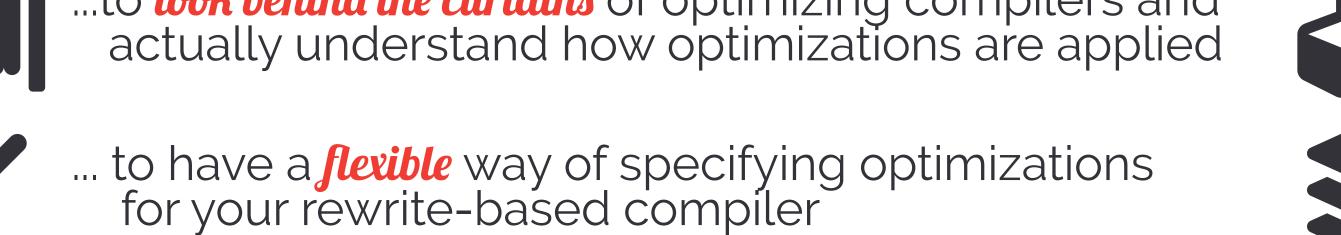


A Language for Describing Optimization Strategies

Wouldn't it be great...



...to *look behind the curtains* of optimizing compilers and actually understand how optimizations are applied





... to build custom optimizations in an *extensible* language while avoiding to rely on fixed scheduling APIs



... to use a *scalable* approach that hides complexity behind high-level abstractions

Optimizing Programs like it's 1998 2019

Visser et. al.: Building program optimizers with rewriting strategies (ICFP 1998)

Core Concepts

A **Strategy** encodes a program transformation type Strategy[P] = P → RewriteResult[P]

A *RewriteResult* encodes its success or failure RewriteResult[P] = Success[P](p: P) Failure[P](s: Strategy[P])

Examples

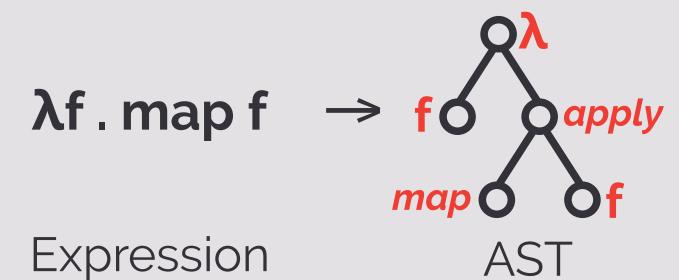
def id[P]: Strategy[P] = (p:P) \Rightarrow Success(p) def fail[P]: Strategy[P] = (p:P) ⇒ Failure(fail) ...and language-specific: $map(f) \circ map(g) \rightarrow map(f \circ g)$ **def** mapFusion: **Strategy**[LIFT] = $p \Rightarrow match$ { case map(f) \circ map(g) \Rightarrow Success(map(f \circ g)

Combinators

Strategy[P] ⇒ Strategy[P] ⇒ Strategy[P]

= fs ⇒ ss ⇒ p ⇒ fs(p).flatMapSuccess(ss) **Choice**: Strategy[P] \Rightarrow Strategy[P] \Rightarrow Strategy[P] \Rightarrow Strategy[P] = fs \Rightarrow ss \Rightarrow p \Rightarrow fs(p).flatMapFailure(ss) : Strategy[P] \Rightarrow Strategy[P] = s \Rightarrow p \Rightarrow (s \leftrightarrow id)(p) repeat : Strategy[P] \Rightarrow Strategy[P] = s \Rightarrow p \Rightarrow try(s; repeat(s))(p)

Traversals: Where to apply a strategy?



Generic one-level traversals: Strategy[P] → Strategy[P]



....and language-specific: traversals

def body(s: Strategy[LIFT]): Strategy[LIFT] = $p \Rightarrow match$ { case $\lambda x.b \Rightarrow s(b).mapSuccess(nb \Rightarrow \lambda x.nb)$ case _ ⇒ Failure(body(s))

Complete Traversals + Normalization

topdown: Strategy[P] \Rightarrow Strategy[P] = s \Rightarrow p \Rightarrow (s \leftrightarrow one(topdown(s)))(p)

try { : Strategy[P] ⇒ Strategy[P] = s ⇒ p ⇒ (all(tryAll(try(s))); try(s))(p)

Case Studies:

Automatic Differentiation C



Efficient Differentiable Programming in a Functional Array-Processing Language

F achieves efficiency by ICFP'19 rewriting differentiated code

...the strategy for applying rewrite rules can become tricky.

lenRule = length (build
$$e_0 e_1$$
) \Rightarrow e_0

def lenRule: $Strategy[\widetilde{\mathbf{F}}] = p \Rightarrow match {$ case length(build(e_0, e_1) \Rightarrow Success(e_0) ⇒ Failure(lenRule)} case _

¥ ELEV/\TE

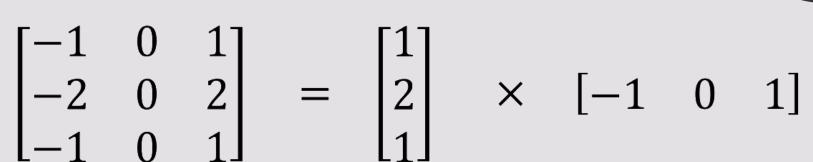
Example 5 (Simplification): $(M^T)^T = M$ $norm(lenRule <+ ...)((M^T)^T) =$

Tracing shows 12 rule applications

Success(M)

Flexible: ELEVATE is able to implement and optimize exisiting rewrite systems

Image Processing



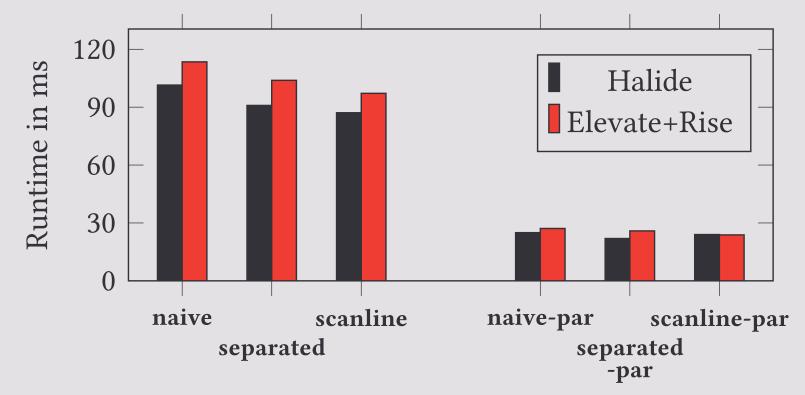
Separable Convolution: Sobel Filter

requires modification of the algorithm instead

Not expressible as a schedule in Halide!

λw::(3.3.float).λimg::(N.M.float).img ▷ $pad2D(1) \triangleright slide2D(3)(1) \triangleright map2D($ λnbh.dot(join(w))(join(nbh))))))) 2D Convolution in Rise (LIFT-like language)

(topdown(separateDot); lowerToC)(conv) Separating Convolution using ELEVATE



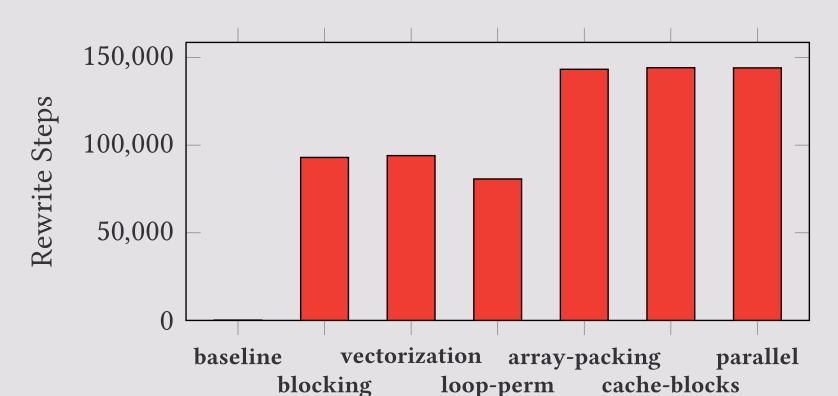
Extensible: ELEVATE can be extended with custom domain-specific optimizations

Deep Learning



Implementing TVM's scheduling language:

xo,yo,xi,yi= s[C].tile(C.op.axis[0], C.op.axis[1], 32, 32) = s[C].op.reduce_axis = s[C].split(k, factor=4) s[C].reorder(xo, yo, ko, ki, xi, yi) Blocking Schedule for Matrix Multiplication in TVM val blocking = (topdown(tile(32,32)); topdown(isReduce ; split(4)); topdown(**reorder**(Seq(1,2,5,6,3,4)))) (blocking ; lowerToC)(mm) Blocking Strategy for Matrix Multiplication in ELEVATE



Scalable: ELEVATE hides 100k's of rewrite steps behind high-level abstractions

