Future Directions for Optimizing Compilers

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1 Introduction

As software becomes larger, programming languages become higher-level, and processors continue to fail to be clocked faster, we’ll increasingly require compilers to reduce code bloat, eliminate abstraction penalties, and exploit interesting instruction sets. At the same time, compiler execution time must not increase too much and also compilers should never produce the wrong output. This paper examines the problem of making optimizing compilers faster, less buggy, and more capable of generating high-quality output.

1.1 Why are Compilers Slow?

While very fast compilers exist,\textsuperscript{3} heavily optimizing ahead-of-time compilers are generally not fast. First, many of the sub-problems that compilers are trying to solve, such as optimal instruction selection, are themselves intractable. Second, after performing basic optimizations that are always a good idea, and that usually reduce code size, a compiler is confronted with optimization opportunities (auto-vectorization, loop unrolling, function inlining, etc.) that have a less clear payoff and that often increase the amount of code that has to be subsequently processed. Third, the compiler would like to reach a fixed point where every obviously desirable transformation has been performed; there is rarely enough time to do this. Finally, fully breaking down the abstractions in high-level-language code is not an easy job.

1.2 Why are Compilers Wrong?

Compiler bugs have diverse root causes:

- Difficult-to-avoid pitfalls in unsafe compiler implementation languages—commonly, null pointer dereferences and use-after-free errors.
- Little-used and unclear corner cases in the language standards. For example, C and C++’s integer promotion rules\textsuperscript{4} and volatile qualifier [9] have caused trouble.

\textsuperscript{3} https://bellard.org/tcc/tccboot.html
\textsuperscript{4} https://blog.regehr.org/archives/482
Little-used and unclear corner cases in the compiler intermediate representation (IR) semantics. To support aggressive optimizations, compiler IRs have evolved sophisticated notions about undefined behavior that are error prone and also have typically not been formally specified or even documented adequately [18].

Failure to correctly handle corner cases while implementing an optimization. Peephole optimizations, in particular, seem difficult for people to reason about; LLVM’s peephole optimizer was its buggiest file according to Csmith [34].

Failure to respect an invariant on a compiler data structure. These invariants are often quite sophisticated and are not always well-documented.

Complexity and shortcuts that are a consequence of trying to make the compiler go fast. For example, caching results instead of recomputing them is error-prone when the results may be invalidated in a fine-grained way.

Code churn due to external requirements such as new language standards, new targets and target features, and improved optimizations. The global impact of new externally-motivated features is not always clear at first.

Taken together, these factors seem to make compiler bugs a fact of life. Also, while compilers are on the face of it eminently testable (their job is well-understood, they are deterministic, they run reasonably quickly, and they have few external dependencies), they often seem to be under-tested, since buggy behaviors can usually be triggered by small, innocuous-looking inputs.

1.3 Why is the Quality of Generated Code Sometimes Poor?

An optimizing compiler is faced with a collection of intractable search problems and given very little time in which to solve them. The solutions to these problems enable and block each other in ways that can be difficult to predict ahead of time: this is the “phase ordering” problem where a compiler must find a sequence of optimization passes that seems to give good results most of the time, without taking too long to execute. Optimizations that work well in one problem domain (loop vectorization or aggressive partial evaluation, for example) are often useless or counterproductive in other domains, and yet a given compiler instance has no obvious principled way to know what will work well this time.

Moving up a level of abstraction, compiler development teams are faced with many demands on their time—fixing bugs, supporting new language features, supporting new target features, dealing with Spectre and Meltdown, etc.—besides working on new optimizations. Little has been written about the economics of compiler optimization (Robison’s 2001 paper [24] is the exception), but it is obvious that economics is decisive in determining what we can accomplish in this space.

An important part of high-quality code generation is optimizing predictably: a computation should be converted into high-quality machine code regardless of its context and how it is expressed in the language syntax. A partial solution to predictable optimization is aggressive normalization of IR. Lawrence [17] says:
Normalization refers to where many different source programs result in the same machine code after compilation—that is, where the same machine code is produced regardless of which form was written by the programmer.

Normalization is an important, useful property of an IR. However, in this paper we explore a different approach to predictability: finding optimizations using aggressive search algorithms and SMT solvers that are, unlike humans, not easy to fool with superficial changes of representation.

Proebsting’s Law\(^5\) states that performance gains due to improvements in compiler optimizations will double the speed of a program every 18 years. This allusion to Moore’s Law was funnier back when we were seeing massive performance increases every year due to hardware. Nevertheless, Proebsting’s Law—which comes out to 4\% per year—likely overstates performance gains due to compiler optimizations. The obvious experiment that would validate or refute this law is easy to perform over a span of a few years, but would be difficult over longer time frames since a fixed platform and benchmark suite has to be supported by the compiler under test for the duration of the experiment. An obvious but wrong way to examine Proebsting’s Law would be to look at the size of the performance gap between unoptimized and optimized code over time. This doesn’t work because “unoptimized” doesn’t have an objective meaning.

If even 4\% per year is too much to expect from compiler technology, is it still worth working on optimizers? Pugh\(^6\) and Bernstein\(^7\) have argued that it isn’t. On the other hand, given users’ evident preference for fast code, it isn’t clear that these arguments—which were perhaps unserious to begin with—hold any water, and in any case getting high-performance executables out of high-level languages seems to fundamentally require aggressive compiler optimization.

## 2 Semantics, Solvers, Synthesis, and Superoptimizers

This paper is organized around a handful of thesis statements; the main one is:

\textit{Thesis 1.} Major components of future compilers will be generated partially automatically, with the help of SMT solvers, directly addressing compiler speed (automatically discovered optimizations will be structured uniformly and amenable to fast rewrite strategies), compiler correctness (automated theorem provers are generally less fallible than humans), and code quality (solvers can be used to conduct a thorough search of the optimization space).

Key ingredients in realizing this idea are formal semantics for the languages being optimized, use of SMT solvers to verify equivalence or refinement, and effective

\(^5\) [http://proebsting.cs.arizona.edu/law.html](http://proebsting.cs.arizona.edu/law.html)

\(^6\) [http://www.cs.umd.edu/~pugh/IsCodeOptimizationRelevant.pdf](http://www.cs.umd.edu/~pugh/IsCodeOptimizationRelevant.pdf)

\(^7\) [http://cr.yp.to/talks/2015.04.16/slides-djb-20150416-a4.pdf](http://cr.yp.to/talks/2015.04.16/slides-djb-20150416-a4.pdf)
synthesis algorithms to create optimized code in cases where brute-force search
doesn’t work.

An easy place to start is the collection of rewrite rules that most optimizing
compilers use to remove local inefficiencies. For example, this line from the Go
compiler:

\[(Xor 64 x (Xor 64 x y)) \rightarrow y\]

looks for code like this:

```go
func foo(x int, y int) int {
    return x ^ (x ^ y)
}
```

and optimizes it to simply return \(y\). The optimization isn’t written in Go,
but rather in a domain-specific language (DSL) for pattern rewrites. At the time
the Go compiler is compiled, the DSL is translated into Go and then compiled
along with the rest of the compiler source code. The compiler for the Mesa shader
language contains an analogous collection of rules, such as this one that takes
advantage of one of De Morgan’s Laws:

\[\neg a \land \neg b \rightarrow \neg(a \lor b)\]

GCC specifies similar transformations using a Lispish language:

```c
/* PR53979: Transform ((a ^ b) | a) -> (a | b) */
(simplify
    (bit_ior:c (bit_xor:c @
        @
        ) @
    )
    (bit_ior @
        @
    )
)
```

Alas, not all compilers have lifted their peephole optimizations into a form
that can be conveniently separated from the rest of the compiler. For example,
LuaJIT has 2,300 lines of C to do this job, libFirm has 8000 lines, and
LLVM’s instruction combiner (InstCombine) probably wins the prize for the
strongest and most baroque IR-level peephole optimizer ever created, at 30,000
lines of C++. Also, GCC has many transformations that aren’t specified in
match.pd but rather appear explicitly in code.

Two threads of research will help us improve upon existing peephole optimizers.
First, compiler developers and researchers should:

\[\text{https://github.com/golang/go/blob/go1.10.1/src/cmd/compile/internal/ssa/gen/}
\text{generic.rules#L661}\]

\[\text{https://github.com/mesa3d/mesa/blob/master/src/compiler/nir/nir_opt_}
\text{algebraic.py#L351}\]

\[\text{https://github.com/gcc-mirror/gcc/blob/gcc-8.1.0-release/gcc/match.pd#}
\text{L709}\]

\[\text{https://gcc.gnu.org/onlinedocs/gccint/The-Language.html}\]

\[\text{https://github.com/LuaJIT/LuaJIT/blob/master/src/lj_opt_fold.c}\]

\[\text{https://github.com/libfirm/libfirm/blob/master/ir/opt/iropt.c}\]

\[\text{https://github.com/llvm-mirror/llvm/tree/master/lib/Transforms/InstCombine}\]
1. Create a declarative language for writing IR-level optimizations.
2. Implement solver-based tools for finding incorrect optimizations, not-weakest
   preconditions, groups of optimizations that either subsume each other or
   undo each other, etc.
3. Implement a compiler-compiler with the goal of generating specialized code
   that can perform the specified optimizations scalably: the runtime of the
   optimizer should be a sublinear function of the number of optimizations and
   the constant factor should be small. This is important for both JIT and AOT
   compilers.

Although several compilers (as we have seen) have taken step 1 in this list, much
work remains to be done for items 2 and 3. A highly useful side effect of writing
a verifier is that it forces a formal specification of IR semantics to be written.
Most IRs are only informally specified, guaranteeing the existence of dark corners
in the semantics.

The second research thread is to:

1. Derive new optimizations either from first principles or by looking for optimizations
   that are missed in practice. The details of the search procedure aren’t
   important: it could be randomized, enumeration-based, or counter-example
   guided inductive synthesis (CEGIS). The tool that discovers optimizations
   using an expensive search is called a superoptimizer.
2. Express the discovered optimizations in a suitably general form, with appropriate
   preconditions, in the declarative language.
3. Iterate until a large fraction of expressible, profitable optimizations are
   performed by the compiler.
4. Increase the expressiveness and reach of declarative optimizations, with the
   goal of replacing more and more hand-written compiler code over time. Similar
   ideas can be used to help automate the construction of parts of the compiler
   other than peephole optimizations, but we’ll discuss them later.

Here, again, there has been some progress but much work remains.

Figure 1 shows the big picture: a feedback loop that makes the compiler more
effective at compiling the code it is given. The proposed feedback loop is unlike
profile-guided optimization, which optimizes a program based on its own observed
execution characteristics. The proposed feedback loop is also dissimilar to most
existing research on applying machine learning to compilers, which typically
focuses on improving heuristics (phase ordering, function inlining thresholds, etc.)
rather than on deriving entirely new optimizations.

This overall vision is not new, but rather builds on a compact body of work that perhaps began in 1979 when Fraser [11] described a portable peephole optimizer:

Given an assembly language program and a symbolic machine description,
PO simulates pairs of adjacent instructions and, where possible, replaces
them with an equivalent single instruction.
Fig. 1. The big picture

| Compiler | Object Code | Source Code | Code Fragments, Patterns, Statistics |
|----------|-------------|-------------|-------------------------------------|

formal semantics for source, IR, and assembly langs

performance models, experiments on real hardware, etc.

source code

generated code

solver-assisted offline code generation

code fragments, patterns, statistics

object code

Table 1. Some superoptimizers

| Name              | Sound? | Target Language | LHS Extraction | Search Method |
|-------------------|--------|-----------------|----------------|---------------|
| Fraser [11]       | yes    | asm             | control flow   | exhaustive    |
| Davidson and Fraser [7] | yes    | asm             | data flow      | exhaustive    |
| Massalin [21]     | no     | asm             | by hand        | exhaustive    |
| Denali [16]       | yes    | Alpha           | by hand        | synthesis     |
| Bansal and Aiken [2] | yes    | x86             | control flow   | exhaustive    |
| Sands [a]         | no     | LLVM IR         | data flow      | exhaustive    |
| STOKE [27]        | yes    | x86-64          | by hand        | randomized    |
| Optgen [3]        | yes    | FIRM IR         | data flow      | exhaustive    |
| Souper [25]       | yes    | LLVM IR         | control + data | synthesis     |

[a] https://www.youtube.com/watch?v=8TLbP_XTJWQ

STOKE [27] | yes | x86-64 | by hand | randomized |
Optgen [3] | yes | FIRM IR | data flow | exhaustive |
Souper [25] | yes | LLVM IR | control + data | synthesis |

Table 1. Some superoptimizers
This work is particularly impressive given that automated theorem provers were primitive when it was published.

Table 1 summarizes the design points of some prior work. A superoptimizer is sound if (leaving aside implementation defects) it only derives correct optimizations. Unsound tools—that sometimes derive incorrect optimizations—exist because it may be much faster to simply test the original and optimized code against each other, rather than invoking an automated theorem prover. Bansal and Aiken’s tool [2] used a hybrid strategy: it rapidly ruled out obviously incorrect optimizations via testing but fell back on a solver to achieve soundness. A blog post by Sharp\(^\text{14}\) contains additional discussion of search-based code generation.

Historically, most work on peephole optimization has been at the level of machine instructions, with the goal of cleaning up routine inefficiencies emitted by relatively simple code generators. On the other hand, in 1982 Tanenbaum [30] said that

\[\ldots\text{it is desirable to do as much optimization as possible on the intermediate code, because that optimizer can be written once and for all and used without change as a filter for subsequent front ends and back ends.}\]

In practice it looks like IR and backend superoptimizers are both useful and desirable; we’ll have more to say about this later.

The left-hand side (LHS) of a compiler optimization is the code that will be optimized. The “LHS extraction” column of Table 1 answers the question: How does the superoptimizer extract the program fragments that it will attempt to optimize? The easiest answer is “this is done by hand,” which is suitable for superoptimizers like STOKE and Massalin’s that are primarily aimed at aiding assembly language programmers and library developers. For a superoptimizer that runs as part of a compiler, extraction may be via control flow (adjacent instructions are optimized) or data flow (dependent instructions are optimized). The latter is likely to be more effective, since it is insensitive to accidents of instruction layout, but the former strategy may be useful in particularly simple or just-in-time optimizers. The search method is how a superoptimizer finds the cheapest right-hand side that refines the given LHS.

### 3 Case Study Part 1: Declarative Peephole Optimizations for LLVM

As a running example, let’s look at taking \(((x << 31) >> 31) + 1\), an inefficient idiom for isolating and flipping the low bit of a signed 32-bit integer, and rewriting it as \(-x \& 1\). In LLVM IR, the LHS of this optimization is:

\[
\begin{align*}
%2 &= \text{shl} \ i32 \ %0, \ 31 \\
%3 &= \text{ashr} \ i32 \ %2, \ 31 \\
%4 &= \text{add} \ \text{nsw} \ i32 \ %3, \ 1
\end{align*}
\]

\(^{14}\) https://jamey.thesharps.us/2017/06/19/search-based-compiler-code-generation/
and the RHS is:

\[
\begin{align*}
%2 &= \text{xor } i32 %0, -1 \\
%3 &= \text{and } i32 %2, 1
\end{align*}
\]

In InstCombine, this optimization, which depends on executing in a context where the current instruction is already known to be adding one to \( \text{Op0} \), is:

```cpp
const APInt *C;
if (match(Op0, m_AShr(m_Shl(m_Value(X), m_APInt(C)), m_APInt(C3))) &&
    C2 == C3 && *C2 == Ty->getScalarSizeInBits() - 1) {
    Value *NotX = Builder.CreateNot(X);
    return BinaryOperator::CreateAnd(NotX, ConstantInt::get(Ty, 1));
}
```

The transformation has two parts: a condition that looks for optimizable code (e.g., the \text{m\_AShr} function pattern-matches an arithmetic right-shift) and a body that creates new instructions to replace the old ones.

Problems that stem from writing peephole optimizations in C++ include:

- Since shared computations are factored out of optimizations for efficiency, there is substantial entanglement across optimizations.
- Automated verification of transformations written in imperative code is challenging. Verification is desirable because InstCombine transformations are very easy to get wrong.
- Optimizations contain individual, customized reasoning about profitability, making it difficult to maintain consistency or to experiment with alternate profitability heuristics.
- There exist groups of optimizations that are individually unprofitable, that become profitable when they can be performed together. LLVM’s recognition of these situations, and its ability to act upon them, is ad hoc at best.
- Many optimizations conservatively and unnecessarily drop instruction attributes about undefined behavior; a formal verification tool can easily tell developers when these flags can be preserved or added.
- Since its application strategy is entwined with its transformations, speeding up InstCombine is not easy.
- Termination problems can occur when optimizations undo each other [22].

The declarative optimization language needs to be easy for LLVM developers to read and write, and it must allow a collection of tools to be written around it. Alive [20] is an example of what such a language could look like; in it, the optimization above is:

```alive
Pre: C == width(%in) - 1
%1 = shl %in, C
%2 = ashr %1, C
%out = add %2, 1
=>
%3 = and %in, 1
%out = xor %3, 1
```
Although Alive was primarily designed for expressiveness and formal verification, we also conducted an experiment in automatically converting Alive patterns into C++ code performing the specified optimizations. This worked, but the generated code simply iterated over the rules; there is much room for improvement in terms of factoring out common code, detecting collections of optimizations that need to be applied together, etc. A suitable framework for this might be a multiple subtree matching algorithm \cite{one, two}, similar to well-known automata-based substring matching techniques; it automatically avoids duplicated work when similar subtrees are being searched for. The automaton will be generated from the list of declarative optimizations at compiler-compile-time.

Another problem that can be solved naturally within this framework is recognizing optimizations that are resistant to the greedy application strategy because they are unprofitable individually but profitable when performed together. We’ll use this function to illustrate the issue:

```c
unsigned foo(unsigned a, unsigned b) {
    unsigned na = -a;
    unsigned nb = -b;
    unsigned c = na - nb;
    unsigned d = na + nb;
    return c ^ d;
}
```

This trivially compiles into five arithmetic operations:

```c
define i32 @foo(i32, i32) {
  %3 = sub i32 0, %0
  %4 = sub i32 0, %1
  %5 = sub i32 %3, %4
  %6 = add i32 %3, %4
  %7 = xor i32 %5, %6
  ret i32 %7
}
```

At this point, there are two InstCombine transformations that apply. First, \(-a - b\) can be rewritten as \(b - a\), saving two operations. Second, \(-a + -b\) can be rewritten as \(-(a - b)\), saving one operation. The resulting function will contain four arithmetic instructions:

```c
define i32 @foo(i32, i32) {
  %3 = sub i32 %1, %0
  %4 = add i32 %0, %1
  %5 = sub i32 0, %4
  %6 = xor i32 %3, %5
  ret i32 %6
}
```

The problem is that, when considered individually, neither of these transformations looks profitable, because they both add new instructions while not
obviously removing old ones: each of them eliminates uses of \(-a\) and \(-b\) but those values are used by the other code. In cases like this, the author of an InstCombine transformation has two choices. First, avoid performing a rewrite when instructions on the LHS have external uses. Second, go ahead and perform the rewrite, on the optimistic assumption that some other optimization will eliminate the extra uses. In this case, an LLVM contributor made the optimistic assumption and the gamble pays off, allowing InstCombine to produce the four-operation version of this function. However, it is easy to construct code where the optimism is unfounded. This C code (where \(x\) and \(y\) are global unsigned ints):

```c
unsigned bar(unsigned a, unsigned b) {
    unsigned na = -a;
    x = na;
    unsigned nb = -b;
    y = nb;
    unsigned d = na + nb;
    return d;
}
```

compiles to:

```c
define i32 @bar(i32, i32) {
    %3 = sub i32 0, %0
    store i32 %3, i32* @x
    %4 = sub i32 0, %1
    store i32 %4, i32* @y
    %5 = add i32 %3, %4
    ret i32 %5
}
```

and then InstCombine optimistically performs a transformation, increasing the number of arithmetic operations from three to four:

```c
define i32 @bar(i32, i32) {
    %3 = sub i32 0, %0
    store i32 %3, i32* @x
    %4 = sub i32 0, %1
    store i32 %4, i32* @y
    %5 = add i32 %0, %1
    %6 = sub i32 0, %5
    ret i32 %6
}
```

In contrast, we would like a peephole optimization pass to have the property that it never gratuitously adds a useless instruction. A solution is to speculatively perform all possible transformations on a function, tracking which instructions’ use counts go to zero, and then committing only to optimizations that, performed
together, give a global win.\textsuperscript{15} This strategy, however, only works within InstCombine; a more comprehensive approach such as equality saturation \cite{31} will be needed to solve coordination problems across passes. In conclusion:

\begin{center}
\begin{tabular}{|p{1\textwidth|}}
\hline
\textit{Thesis 2.} When possible, compilers should specify rules, machine characteristics, and other regular information in declarative formats, in order to facilitate rapid updating, independent checking, and efficient translation to code that executes when the compiler runs. \\
\hline
\end{tabular}
\end{center}

\section{Case Study Part 2: Superoptimizing LLVM}

Once the declarative language and its associated tooling is in place, we are free to strengthen the optimizer further by writing more rules by hand, without fear of miscompilation or of slowing down the compiler much. So why not stop here? There are several reasons to prefer automated derivation of optimizations. First, LLVM is being targeted by new programming languages: Rust, Julia, and others. Not only is LLVM not particularly tuned to optimize patterns that are commonly produced by frontends for these languages, but also higher-level languages tend to lean more heavily on the optimizer than do C and C++. Second, sometimes we need to adjust the semantics of IR constructs. As of fall 2018 there are undefined-behavior-related issues, that are still being resolved \cite{18}, that are going to eventually invalidate some optimizations currently in LLVM while enabling new, as yet unimplemented, transformations in InstCombine. Third, useful optimizations for C and C++ are still missing. In all of these cases, we can probably find better ways to use compiler developers’ time than reading optimized IR and trying to find missed optimizations in it.

Souper \cite{25} is a superoptimizer for LLVM IR that derives optimizations similar to the ones in InstCombine. Souper works by:

1. Choosing a “root” SSA value that it will attempt to compute more cheaply.
2. Recursively following backwards edges in the SSA graph, extracting instructions until it is blocked by a function entry, a loop, or an unsupported instruction (floating point, function call, load from memory, and a few others). Souper also tracks information learned from diverging and converging control flow edges using, respectively, path conditions and “block path conditions.”
3. Attempting to find a cheaper way to compute the value using counterexample-guided inductive synthesis (CEGIS) \cite{14}.

Eventually, Souper will attempt to optimize every integer-typed SSA value. Since CEGIS is not fast, this can be very time consuming, particularly if the solver is allowed to run for a while before timing out and if we attempt to synthesize relatively large RHSs. However, synthesis results are cached and can subsequently be applied relatively quickly: in a preliminary experiment we saw Souper increasing compile time by about 10% in the warm-cache case, compared

\footnote{https://twitter.com/johnregehr/status/942094482828181504}
to a regular -O3 compile. After compiling LLVM itself (3.5 MSLOC of C++)
Souper’s cache occupies 362 MB of RAM; when dumped to disk, the file is
149 MB. This is acceptable for a research prototype but it isn’t the solution that
we want to deploy.

Returning to the running example, its LHS in Souper IR is very similar to
the LLVM version:

\begin{verbatim}
%in:i32 = var
%1 = shl %in, 31
%2 = ashr %1, 31
%out = addnsw %2, 1
infer %out
\end{verbatim}

Souper’s synthesis produces this RHS:

\begin{verbatim}
%4:i32 = xor 1:i32, %in
%5:i32 = and 1:i32, %4
result %5
\end{verbatim}

This optimization, like every optimization discovered by Souper, is completely
specific: it only applies to one pattern of instructions, one choice of values
for constants, one width of operators, etc. It would be preferable to exploit—
as peephole optimizers written by humans do—the fact that optimizations are
almost always more broadly applicable. Generalization can be done along multiple
axes, here we’ll look at relaxing constraints on bitwidths and choice of constants.
Starting with the optimization derived by Souper above, we can translate it into
Alive like this:

\begin{verbatim}
%1 = shl i32 %in, 31
%2 = ashr %1, 31
%out = addnsw %2, 1
=>
%4 = xor 1, %in
%out = and 1, %4
\end{verbatim}

The i32 bitwidth constraint in the first line suffices to constrain the entire
optimization to the 32-bit case. This optimization can be trivially generalized
by removing the bitwidth constraint and by replacing each constant on the LHS
with a symbolic constant:

\begin{verbatim}
%1 = shl %in, C1
%2 = ashr %1, C2
%out = addnsw %2, C3
=>
%4 = xor 1, %in
%out = and 1, %4
\end{verbatim}

The problem with this more generic optimization is that it doesn’t work for all
choices of constants: it requires a precondition check before it can fire safely
Menendez and Nagarakatte [23] showed that it is possible to automatically derive weakest preconditions for Alive optimizations. For this example, their tool, Alive-Infer, comes up with:

$$(((\neg C_2 \lor \neg C_1) == \text{-width}(%\text{out})) \& \& (C_3 == 1))$$

Although this looks a little funny, and it isn’t minimal in terms of operations performed, it is indeed a weakest precondition for the optimization to fire.

There are other dimensions along which an optimization can be generalized. It is sometimes the case that when LLVM’s undefined behavior qualifiers are present on the LHS, they can be preserved on the RHS. The declarative optimization language should (as Alive does) specifically support automatically tagging RHSs with as many of these flags as soundness allows. Another form of generality is found in optimizations that want to perform similar transformations across a range of different instructions. For example, in InstCombine it is common to see an optimization involving comparison instructions that is parameterized by the comparison type. This could be supported in the optimization language using a regular-expression-like mechanism, or alternatively we could simply require each pattern to be specified separately.

Souper appears to be good at a few things besides finding peephole optimizations. First, it can robustly recognize idioms such as rotate and Hamming weight computation that span multiple instructions. In contrast, compiler idiom recognizers tend to be fragile. For example, whereas optimizing C and C++ compilers have often been good at turning the obvious code

$$x \ll r \lor x \gg (32 - r)$$

into a 32-bit rotate-left instruction, they generally failed to recognize the slightly more complicated code that must be used to avoid undefined behavior in the rotate-by-zero case.16 Idiom recognition is useful when a source or intermediate language does not support direct expression of the idiom. Souper is good at this because the SAT solver is effective at deobfuscating whatever code ends up being written by humans. Second, Souper is good at finding dead code; we’ve seen Souper reduce the size of a Clang executable by about 3 MB (4.4%).

In summary, although many of the pieces are in place, a superoptimizer-generated InstCombine replacement for LLVM will require both research and engineering work. On the other hand, a more limited goal—a research prototype replacing InstCombine with the Souper LLVM pass, omitting the generalization, fast matching, and declarative optimization language—is within easy reach.

Souper itself has many areas that need improvement. It should support memory instead of living only in the SSA world. It should support vector instructions, floating point instructions, loops, and it should look across function boundaries. Finally, Souper is sometimes limited by the capabilities of the SMT solver, particularly when divisions or floating point operations are involved (an extremely preliminary FP-aware Souper prototype exists). In summary:

16 https://blog.regehr.org/archives/1054 and https://blog.regehr.org/archives/1063
5 Synthesizing More of Compilers Automatically

The scope of an IR→IR superoptimizer is limited; it cannot exploit target-specific optimizations such as fun addressing modes, nor does it have access to PL-level information, such as types, that is often necessary to perform higher-level optimizations. How can we get solver-driven optimization at higher and lower levels than IR? The answer is clear: more superoptimizers.

The case for target-aware superoptimization has already been made in the context of offline tools that come up with suggestions for compiler implementors. For example, Granlund and Kenner [13] report that with the GNU superoptimizer:

A number of surprising results were obtained, many of which were unknown to the architects of the RS/6000 processor.

Another technique with a long history is facilitating the development of compiler backends by writing incomplete machine descriptions in a declarative language, instead of embedding this information in imperative code. LLVM and GCC both do this. These descriptions serve as a partial solution to the never-ending tasks of creating a backend for each CPU or GPU target that must be supported, and adjusting and retuning these backends with new pipeline models, auxiliary instructions, etc. as new micro-architectures are released. A logical step forward would be to augment these structural instruction descriptions with formal semantics of the instructions being described, as a step towards solver-based generation of major backend components such as instruction selectors. This idea has been explored in a number of research projects [4, 8, 15]. A goal for future work is to automate the construction of as much of a compiler backend as possible. In situations where compile time is not a significant constraint, a solver can be used in an online fashion, allowing optimality guarantees to be made. However, in the common case the backend will need to be generated offline, even if this results in missed code generation opportunities.

Some compilers have a language-specific IR, such as Rust’s MIR and Swift’s SIL, that is intended to facilitate optimizations that require more source-level information. These should be targeted by superoptimizers. In other words:

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\[\text{https://llvm.org/docs/TableGen/index.html}\]
\[\text{https://gcc.gnu.org/onlinedocs/gccint/Machine-Desc.html#Machine-Desc}\]
\[\text{https://blog.rust-lang.org/2016/04/19/MIR.html}\]
\[\text{https://github.com/apple/swift/blob/master/docs/SIL.rst}\]
Every IR in a compiler, and every translation between representations, is an opportunity for superoptimization.

Beyond front-end, middle-end, and backend optimizers, more parts of compilers can be generated with help from solvers. For example, optimizers rely heavily on static analyses, which can be viewed as ad hoc, domain-specific automated theorem provers. For instance, LLVM has “basic alias analysis,”\(^\text{20}\) that uses relatively simple rules to reason about pointers, and also value tracking, which attempts to prove that individual bits have fixed values.\(^\text{21}\) Each of these solvers takes a collection of rules that express locally obvious properties of code (e.g., “a pointer to a freshly allocated memory block cannot alias any existing block”) and pushes them around the program with the goal of, for example, proving that a store instruction does not write to the same memory region as another store.

The alias analysis rules in LLVM are embedded in the C++ code implementing the pass. Alternatively, these rules could be written mathematically. This will make it easier to prove that each rule is consistent with the semantics of LLVM IR, while still being possible to automatically generate C++ code that implements a given analysis that propagates those rules.

Static analysis rules themselves can also be generated automatically [26]. Given the semantics of the IR and the semantics of the result of the analysis, one can use an SMT solver to automatically generate the most precise transfer functions that implement the analysis.

6 Data-Driven, not Intuitive, Compiler Design and Implementation

As large, complex artifacts, compilers have significant inertia: they are better at compiling yesterday’s programs for yesterday’s architectures than they are for solving today’s problems. As we heard a GCC developer say: “it’s like piloting a supertanker—we can steer, but it takes a really long time to change direction.” The inertia is rooted in thousands of little design decisions that ossify once they get implemented. For example, consider a relatively simple compiler component: a conservative static analysis of the values that an integer-typed variable might take. Before implementing this analysis we’ll need to decide:

- Should it be lazy or eager?
- Should its results be cached and, if so, at what granularity should the cache be invalidated?
- Should integer ranges be allowed to wrap?
- Should the analysis be relational?
- Should it be flow, context, or path sensitive, and if so to what degree?

\(^\text{20}\) https://github.com/llvm-mirror/llvm/blob/release_60/lib/Analysis/BasicAliasAnalysis.cpp

\(^\text{21}\) https://github.com/llvm-mirror/llvm/blob/release_60/lib/Analysis/ValueTracking.cpp
Should it attempt to retain precision when confronted with bitwise operators, and if so how hard should it try?

Etc.

Answering these questions requires a detailed understanding of how the analysis results will be used, the characteristics of the programs being analyzed, and the available resources at compile time. Some of the answers will be based on experimental data but others will come from a developer’s intuition. Eventually the developer will move on to other jobs and at the same time there will be drift in the character of the programs being compiled, the target architectures, and the rest of the compiler’s structure and capabilities. As a specific example, many design and implementation decisions in LLVM boil down to a guess that Chris Lattner made ca. 2007; some of these have aged well while others have not.

A compiler solves both hard and soft problems. A hard problem is one where a mistake threatens the compiler’s correctness. The implementation of almost any optimization or static analysis involves solving hard problems. A soft problem is one where a mistake potentially affects the resource usage of the compiler or the compiled program, but does not threaten correctness. Soft problems include deciding which optimization passes to run and in what order, which specific optimizations to perform, how hard a static analysis should try to reach a useful conclusion, etc. This leads to:

**Thesis 5.** A data-driven approach should be used to solve both hard and soft problems in compilers.

Sources of data include the programs being compiled, execution characteristics of these programs on targets of interest, and execution characteristics of the compiler itself. Hard problems are best attacked by discrete methods such as automated theorem provers. Soft problems are best attacked by continuous methods such as combinatorial optimization and machine learning.

A part of a compiler is data-driven if, given enough data, it can automatically and rapidly (perhaps within a few hours or days) be re-tuned to fit new circumstances. Most parts of most current compilers do not meet this criterion.

Although hard compiler problems can be solved using data—the scenario in Section 4 where Souper is used to synthesize missing optimizations is an example—soft problems are the more obvious targets. For example, effective compilation of modern C++ requires good heuristics about when to inline a function call. These heuristics are relatively difficult to get right and are not often considered to be completely satisfying. Moreover, when LLVM gets targeted by a new language, such as Rust or Julia, or is itself retargeted to a new platform, such as an MSP430 with extreme code size constraints, it is not trivial to retune the inliner for the new situation. A data-driven approach to inlining would, in contrast, run many experiments in order to derive an inlining strategy that maximizes an objective function such as “make Julia code fast” or “reduce code size on an MSP430.” These experiments will require a large amount of input code and may be computationally expensive, but they can operate on a time scale that
is a small fraction of that required for a significant engineering effort. Considerable research exists on the data-driven approach to solving soft compiler problems, including finding a good phase order \[12\], automatic heuristic generation \[29\], and algorithm autotuning \[1\].

7 We Need First-Class Formal Semantics

Many important program representations such as C, C++, x86, and the IRs for LLVM, GCC, and Visual C++, either lack a formal semantics or else lack a first-class formal semantics. This situation impedes the development of formal-methods-based tools because the authors of these tools are forced to formalize a program representation before implementing the tool itself. The resulting semantics tend to be one-offs: they are embedded in a tool, tailored for a specific purpose, and usually cannot be easily reused. The process of formalization is itself (ironically) error-prone and, worse, it often exposes latent ambiguities in real-world systems that can be hard to resolve definitively. For example, our work on undefined behavior in LLVM IR \[18\] ran into this kind of issue, and several years later we’re still working with the LLVM community to get them resolved.

A first-class formal semantics is one that:

- Stands on its own, independent of any particular tool or use case.
- Is widely agreed to be authoritative: any defect in the semantics is fixed with high priority and deviations from the semantics are incorrect by definition.
- Is at the root of an ecosystem of mechanically derived artifacts: documentation, simulators, parsers, static analyzers, compilers and decompilers, etc.
- Has clients both above and below in the tool stack. For example, an x86 semantics is used from above when proving a compiler backend correct, and is used from below when proving that a chip faithfully implements the architecture.
- Has people whose job descriptions include taking care of it: answering questions, keeping it up to date, refactoring it to make it easier to use, writing special-purpose tools to look for missing cases, vacuous elements, and other defects.

These criteria are met, or nearly met, by a semantics for version 8.3 of the Arm architecture.\(^{22}\) In some cases, the technology necessary to create a usable first-class formal semantics may not yet exist, and in other cases the cost of creating the semantics will not be small. For example, C++ probably has both of these problems.

Thesis 6. Durable interfaces, such as ISAs, IRs, and programming languages, should be accompanied by first-class formal semantics.

\(^{22}\) https://alastairreid.github.io/arm-v8_3/
An important use case for formal semantics is translation validation: a proof that a compiler’s output refines its input. The huge advantage of translation validation over invasive proofs of compiler correctness is that translation validation does not ask compiler developers to discharge proof obligations. Therefore, compiler users with high confidence requirements (e.g., those developing avionics software) and compilers users with lower confidence requirements can share the same compiler infrastructure, and only the high-confidence users need to pay the increased tool development and CPU time costs of translation validation.

In principle, a separate translation validation tool is unnecessary when a compiler is made of verified pieces. In practice, it is going to be a long time before all of the pieces are verified: there are many ways to go wrong while composing verified transformations (particularly when the implementation language is unsafe), and also a redundant end-to-end check provides some defense in depth against otherwise-undetected defects.

Translation validation isn’t only for high-confidence use cases, it is also a natural fit for a compiler testing campaign. The process is easy: compile a piece of code (either extracted from applications or generated automatically) and then try to prove that the optimized code refines the original code. We found several LLVM bugs by doing this for small, automatically generated functions.\(^\text{23}\)

Compiler bugs can be very difficult to flush out with testing; our experience is that translation validation tools can be an effective way to find these bugs, though of course the problem of triggering the buggy compiler optimizations remains.

8 Pushing Solver-Based Compiler Implementation Further

Integrated analyses. Typically, a static analysis is based on an abstract domain such as integer ranges, polyhedra, or points-to sets. The analysis proceeds by applying a collection of abstract transfer functions, each describing the abstract effect of some concrete part of the program, until a fixed point is reached. In realistic situations, analysis precision is dropped on the floor in cases where two abstract domains could learn from each other, but they have not been taught to do so. Teaching static analyses to learn from each other is a highly demanding task and typically it is only done in very limited cases such as sparse conditional constant propagation: the most precise combination of constant propagation and dead code elimination [33]. On the other hand, solvers are very good at recognizing special cases such as those that allow extra precision to be gleaned from interacting dataflow facts; the resulting integrated analyses will lead to compilers that optimize more robustly and have fewer phase-ordering problems.

Reducing myopia in transformations. Optimizers tend to be very effective when every optimization step is relatively simple and is clearly a good idea. However, not all optimizations have this character: sometimes the local gradient points in the wrong direction and a substantial piece of code must be recognized as

\(^{23}\) https://blog.regehr.org/archives/1510
a whole, so that it can be replaced with something more efficient. Optimizers therefore contain custom code recognizing common implementations for idioms—such as integer overflow checks, rotates, byte shuffles, and Hamming weight computations—that are efficient at the CPU level but cannot be conveniently expressed in most programming languages. This detection, however, is often not thorough: a few patterns that have been seen in practice (or in benchmarks) are detected, but an unknown number of less important codes fail to get the performance benefits because they express the inefficient operations differently. In contrast, solvers are not easily fooled by incidental changes in the structure of a computation and they can be used as the basis for more robust idiom detectors. For example, we have had good luck recognizing Hamming weight computations using Souper (though only when they are loop-free). Inefficient sorting algorithms and numerical algorithms seem like good targets for future work in this direction.

Data structure synthesis. Codes in high-level languages often make heavy use of APIs such as container classes or tensors. However, the particular choices made by library implementors are not always suitable for performance-critical use cases. One workaround is to use customized libraries; for example, LLVM has “small” versions of the C++ set, vector, and other container classes that avoid heap allocation as long as the container does not grow beyond a small, predetermined number of elements. Alternatively, given an API and a collection of profile-like data about how the API is used, we could try to synthesize a more efficient data structure along with its collection of accessors and mutators. Progress in this direction exists but it’s fair to say that it will be a while before developers can routinely replace elements of standard libraries with superior, synthesized alternatives.

User-defined optimizations. One of Robison’s points is that there are many programs that would benefit from domain-specific compiler optimizations, but that the economics of compiler development are often unfavorable. While some parts of this problem will be ameliorated by the data-driven approach—given a sufficient body of code, a compiler specifically tuned for an application niche can be automatically constructed—and other parts have been solved by open source compilers, the basic problem of teaching a compiler new tricks remains. We believe that domain-specific optimization languages and their associated proof machinery, along the lines of the example in Section 3, are a promising approach.

9 Next-Generation IRs

The IR instruction set. Adding an instruction to a compiler IR can be a bit painful: every backend needs to accommodate the new instruction and also various analyses and transformations in the middle-end need to be taught what the new instruction means, or else there will be code quality regressions. In contrast, the parts of a compiler that are derived using a solver will not require this kind of manual adjustment, since their ideas about the meaning of the new
instruction come from its formal semantics, not from code written by people to cope, individually, with each situation in which the new instruction’s meaning is relevant. At the same time that it should be easier to add instructions to a solver-based compiler, the necessity to do so may decrease due to the ease (discussed in Section 8) with which solvers can recognize sophisticated idioms hiding in collections of simple instructions.

Reducing pointer chasing. Since the in-memory version of a compiler IR is typically pointer-intensive, traversing IR requires a lot of indirections. Informal measurements show that on a modern core with exclusive use of a 25 MB cache, an optimizing C++ compile using GCC or LLVM still spends 30–35% of its runtime stalled on memory operations. The pointer-heavy representation follows from the desire to easily edit the IR on the fly using hand-written passes.

Future IRs that are less-often manipulated in ad hoc fashion can be designed to be cache friendly and also suitable for processing using GPUs and GPU-like many-core processors. As an example of this kind of work, Vollmer et al. [32] report that “For traversals touching the whole tree, such as maps and folds, packed data allows speedups of over 2\times compared to a highly-optimized pointer-based baseline.”

Abstraction. Over the years, IRs have tended to become more abstract and amenable to mathematical analysis, retaining fewer and fewer incidental aspects specified by the original computation. For example:

- register transfer language (RTL) [7] allowed peephole optimizers to be machine-independent
- static single assignment (SSA) [6] eliminates some kinds of incidental mutation, making dependency information much easier to discover
- value state dependence graph (VSDG) [17] and related IRs such as sea of nodes [5] don’t store instructions in lists, but rather make all dependencies explicit
- in LLVM IR, integer operations can take any bitwidth, as opposed to being restricted to widths supported by machine instructions.

The general trend is that a more abstract IR can make desirable optimizations more convenient to perform, but then more work is required to convert the code into a readily executable form. A more abstract IR may not always be a win in terms of code quality: we heard an anecdote where a VSDG-like IR turned out to be a showstopper because it would lose instruction ordering information inserted by expert programmers, and then the compiler backend was incapable of independently rediscovering the desirable ordering. Intuitively, we can expect a solver-oriented compiler to be a better match for a more abstract IR, and we can hope that its backends will be smart enough to cope with the additional abstraction.
10 Conclusions

This paper outlines an agenda for making compilers better by incrementally removing hand-written parts and replacing them with components derived using automated theorem provers, formal semantics, and data-driven tools. Although making this happen will require solving many interesting research problems, we have focused on the engineering advantages of the proposed approach, which we believe are clear and significant.

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