Towards Fully Declarative Program Analysis via Source Code Transformation

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Abstract

Advances in logic programming and increasing industrial uptake of Datalog-inspired approaches demonstrate the emerging need to express powerful code analyses more easily. Declarative program analysis frameworks (e.g., using logic programming like Datalog) significantly ease defining analyses compared to imperative implementations. However, the declarative benefits of these frameworks only materialize after parsing and translating source code to generate facts. Fact generation remains a non-declarative precursor to analysis where imperative implementations first parse and interpret program structures (e.g., abstract syntax trees and control-flow graphs). The procedure of fact generation thus remains opaque and difficult for non-experts to understand or modify. We present a new perspective on this analysis workflow by proposing *declarative fact generation* to ease specification and exploration of lightweight declarative analyses. Our approach demonstrates the first venture towards fully declarative analysis specification across multiple languages. The key idea is to translate source code *directly* to Datalog facts in the analysis domain using declarative syntax transformation. We then reuse existing Datalog analyses over generated facts, yielding an end-to-end declarative pipeline. As a first approximation we pursue a syntax-driven approach and demonstrate the feasibility of generating and using lightweight versions of liveness and call graph reachability properties. We then discuss the workability of extending declarative fact generation to also incorporate semantic information.

Keywords: declarative programming, program analysis, program transformation, Datalog, software quality

1. Introduction

Advances in logic programming (Aref et al., 2015) and increasing industrial uptake of Datalog-inspired approaches (e.g., CodeQL (GitHub, 2021; de Moor et al., 2007), Glean (Facebook, 2021)) demonstrate the emerging need for more powerful program analyses, specified simply and declaratively. Fact generation is the process of translating source code to a program model of Datalog propositions (like "variable x is read on line l"). Such facts underpin declarative program analyses that answer queries over program properties (e.g., liveness). Fact generation is typically accomplished by imperative code that first parses the input program according to a known language grammar. Program terms are further resolved to the domain of relevant facts for the analysis, which depends on the input language's syntax and semantics. While it is straightforward to declaratively define a general liveness analysis (all rules and propositions are succinctly specified a-priori), the act of translating source code to facts incurs many degrees of unspoken complexity (e.g., parsing language-specific constructs and resolving semantic properties like types). This complexity invites up front *imperative* (rather than declarative) implementation that recurs per language. The implementation burden contributes to deep, yet narrow support for a single language or small set of languages (e.g., pointer analysis for Java (Bravenboer and Smaragdakis, 2009)). Current approaches lack convenient, declarative processes for translating source code to logic facts in the analysis domain. This impedes prototyping and developing fully declarative analysis pipelines for lightweight and language-general use cases.

Our idea addresses the gap by proposing techniques for *declarative fact generation* by directly translating program source code to Datalog facts. To give an example, consider Listing 1 with a simple arithmetic language (left) and corresponding propositions read, write, and next generated by program statements (right). In Datalog terminology, the propositions on the right establish the extensional database (EDB), which are facts generated by translating the program. The intensional database (IDB) for our liveness analysis comprises the rule live(x, l) which expresses that variable x is live at line l.

```
a = b + c
                                             read(b, 1)
2
                                              read(c, 1)
    b = a - d
                                              write(a, 1)
3
    c = b + c
                                              next(1, 2)
    halt
                                              read(a, 2)
                                              read(d, 2)
 Key: Propositions
                                              write(b, 2)
                                              next(2, 3)
 read(x, l)
  \rightarrow variable x is read on line l
                                              read(c, 3)
 write(x,l)
                                              read(b, 3)
  \rightarrow variable x is written on line l
                                              write(c. 3)
                                              next(3, 4)
 next(i,j)
  \rightarrow line j executes after line i
                                             emptu
```

Figure 1: Example translation of a simple arithmetic language to facts.

Rules for computing the liveness of a variable *x* at line *l* is given by:

```
live(x,l) \leftarrow read(x,l)

live(x,l) \leftarrow live(x,i), next(i,l), \neg write(x,l)
```

That is, a variable x is considered live at l if it is read on line l, or if it is transitively live and not overwritten on line l. This captures the intuitive description that a variable is live if it is read on line l, or we anticipate that it will be read at some point after l in the program's execution, before being potentially overwritten. As an admittedly naive introduction, we might consider regular expressions as a crude way to generate the facts from expressions for our liveness analysis, in lieu of a well-specified parser:

```
(\w+) = (\w+) + (\w+) \longrightarrow read(\$2, ?)
read(\$3, ?)
write(\$1, ?)
next(?, ? + 1)
```

Regular expression capture groups \$2 and \$3 match operands on the right-hand side to populate *read* facts, and the capture group \$1 for the left-hand side variable populates a *write* fact. Some immediate problems stand out in the regular expression approach. For example,

- 1. readability suffers with escape sequences like \+ and repeated patterns like (\w) to match variables
- 2. patterns like \w+ rely on overly simple assumptions on syntax that are unlikely to generalize (e.g., to expressions)
- 3. regular expressions do not natively expose metadata for source code (e.g., there's no easy way to retrieve

the location of matched variables, corresponding to ? in our facts). Such data would have to be accessed via an API in a program script, and invites imperative implementation.

Despite these shortcomings, the regular expression idea prompts whether a more principled parsing approach (e.g., using PEGs (Ford, 2004)) could abstract the translation phase and better implement the idea. Our approach pursues this line of thought. We use Comby (van Tonder and Le Goues, 2019), a lightweight, declarative, and language-aware parsing tool to implement the approach. With Comby, fact generation for our liveness example is expressed with a declarative *match template* (left) and *rewrite template* (right):

```
\begin{array}{lll} \$x = \$y + \$z & \longrightarrow & \texttt{read}(\$y, \$y.line) \\ & \texttt{read}(\$z, \$z.line) \\ & \texttt{write}(\$x, \$x.line) \\ & \texttt{next}(\$x, \$x.line + 1) \end{array}
```

Comby resolves some of the more glaring issues of the regular expression counterpart:

- 1. no escape sequences and intuitive variable metasyntax for binding matched values
- 2. parameterizable matching behavior for lexical terms like variable identifiers or code block structures
- 3. built-in properties for matched values (e.g., \$x.line substitutes \$x's line number).

An off-the-shelf Datalog engine like Soufflé¹ can consume generated these facts directly, allowing to easily express queries like live(x,2) to find which variables satisfying x are live at line 2, or live("b",1) to find all lines where variable b may be live. A more complete liveness construction will involve more rules for language-specific syntax; our example suffices to illustrate that domain-specific rewriting for code structures and metadata present a workable solution for declarative fact generation. In the rest of this article we focus on call graph construction and reachability, and show how the approach generalizes naturally to multiple languages (Go, C, Zig) for this analysis domain.

We cover our approach for handling real-world programs (§ 2) and evaluate fact generation for call graphs on three languages (§ 3). We discuss related work in § 4 and conclude in § 5.

¹ souffle-lang.github.io

2. Approach

As a first approximation, we pursue a purely syntaxdriven approach. In this approach, declarative templates specify syntactic patterns to match and transform source code to Datalog facts. It is worth stating two caveats up front. First, a purely syntax-driven approach cannot account for semantic properties (e.g., type information) that may affect the domain of the analysis. We treat this concern in more detail in § 2.3. Second, our declarative approach emphasizes ease of expressivity and trades precision when interpreting a source input program. I.e., even at the syntactic level, we do not strive to achieve parity with the exacting precision of language-specific compilers or tooling for translating source code to facts. Since our approach is a first step to proposing declarative fact generation, we focus on demonstrating feasibility and surfacing challenges for practical use cases. We show that by making these tradeoffs, a general method for declarative fact generation can make promising progress for declarative analysis, even across multiple languages and syntaxes.

2.1. Declarative syntax matching and rewriting

We implement our approach with Comby,² a tool to declaratively match and rewrite source code syntax, and use it to translate relevant syntactic constructs to Datalog facts. We choose Comby because it provides flexible, declarative abstractions for syntax rewriting while supporting multiple languages. Comby is language-aware and can correctly parse key program features that allow easy execution of our core idea.

Comby is especially suited for matching code blocks and disambiguating code from comments and strings. It provides a mechanism to define custom match syntax and behavior. The following custom Comby definitions and syntax to implement the approach in this article:

- \$x matches words like hello and contiguous well-balanced expression-like syntax like (a + b) or print("hello world"). It stops matching at whitespace boundaries and so does not match a string like a + b. It also does not match unbalanced code syntax like foo) in typical languages where expressions are expected to be well-balanced.
- \$x* matches the same syntax as \$x, but generalizes to match across whitespace and comments. It stops matching within the boundaries of a well-balanced code block or expression. For example,

{\$x*} matches the body of the balanced braces and across new lines, irrespective of whitespace.

- \$x? matches the same syntax as \$x, but makes the match optional.
- "\$x" matches the body of a well-quoted string. Unlike \$x (without quotes), the quoted variety implies that a data string may be any value, including balanced string values that contain unbalanced parentheses, like "item)".

2.2. Real-world application: Call graph reachability

We demonstrate an end-to-end approach by targeting a call graph reachability analysis. We consider three target languages for these analysis: Go, C, and Zig. We use the Soufflé Datalog framework (Jordan et al., 2016) to define and run analyses, which consumes Datalog facts generated by Comby. The rest of this section explains capabilities and specification of declarative rewriting with Comby, followed by declarative Datalog definitions for computing call graph reachability.

```
package main
2
3
    import "fmt"
4
    func one() int {
6
      return 1
7
8
9
    func incr(n int) int {
10
      return n + one()
11
12
13
    func main() {
      fmt.Printf("%d: %d", one(), incr(1))
14
   }
15
```

Figure 4: example.go

We demonstrate a declarative call graph construction with the Go program in Fig. 4. Our objective is to emit facts that assert whether a function directly calls another function. For example, we want to identify that function incr contains a call site of function one on line 10. We represent this relation with a fact edge ("incr", "one"). The full specification to declaratively rewrite source code to edge facts is shown in Fig. 5a and comprises only four lines. We will walk through how this specification operates shortly.

Once we obtain a set of all edge facts, we use Datalog definitions to compute whether a function transitively calls (may reach) another function, represented

 $^{^2 \}mathtt{comby.dev}$

```
func $f(...) $r? {$body*} -> $body
where nested, rewrite $body {
  $c(...) -> edge("$f", "$c").
}
```

(a) Declarative source code rewriting to produce facts (EDB).

```
.decl edge(x:symbol, y:symbol)
.decl calls(x:symbol, y:symbol)

calls(X,Y) :- edge(X,Y).
calls(X,Y) :- edge(X,K), calls(K,Y).
```

(b) Call graph definitions for EDB facts and IDB relations in Soufflé.

Figure 5: A wholly declarative specification to compute simple static call graph relations from Go code syntax.

by the predicate calls(X,Y). Fig. 5b defines these rules in Soufflé, which comprise only four lines. Armed with initial facts, the definitions compute calls relations on-demand, or output all calls facts, representing all relations in the entire call graph. In practical terms, we can compute call graph reachability for any function (e.g., to discover dependencies) or process facts to generate a visual call graph.

We now explain the operation of the rewrite specification in Fig. 5a. To generate edge facts, we start with the following Comby template to match all static functions:

```
func $f(...) $r? {$body*}
```

The metavariable \$f matches the function identifier and \$body* matches the function body within well-delimited braces {...}. The \$r? metavariable optionally matches syntax that specify a return type (like int in our example). Ellipses ... act as an anonymous variable matching the function's parameters, which we don't use for call graph construction. All other syntax matches concretely.

Next, we use a Comby rule to match each call \$c within \$body, and emit the identifier for that call in a fact as edge("\$f", "\$c"). The rule looks like this:

```
where rewrite $body {
  $c(...) -> edge("$f", "$c").
}
```

This rewrite rule overwrites \$body and appends a result every time the pattern \$c(...) matches, emitting an edge fact on a new line for each call site. By default Comby matches \$c(...) only to calls in the top level \$body, and not nested calls. To handle nested calls, we add an additional nested option to the rule that ensures the rewrite rule fires for calls that nest, like the one call nested inside fmt.Printf on line 14 of Fig 4. The value of \$f\$ is substituted for the function identifier in the match template, and is in scope of the rewrite rule.

To output the full set of facts, we simply need to output \$body, which we do by appending -> \$body to the match template. Putting this together, we arrive at the complete

specification in Fig. 5a. This emits the desired facts for example.go in Fig 4.

```
edge("incr", "one").
edge("main", "fmt.Printf").
edge("main", "one").
edge("main", "incr").
```

All together, we run one command line invocation of Comby to generate these facts, then a subsequent command line invocation of Soufflé to consume them and output the analyzed result. We can then query Soufflé for the functions reachable via main with the query calls(main, X) to yield the set of calls {incr, one, fmt.Printf}.

2.3. Complexities for declarative fact generation

Both syntactic and semantic features in modern languages impact the ability to precisely recognize properties to encode in the Datalog domain. Taking call graph reachability as an example, we discuss possibilities for extending syntactic matching, and associated challenges thereof. We then expand on the prospect of incorporating semantic information to overcome hurdles that inhibit more precise declarative specification.

Extending syntax matching. We take Go as a representative modern language that supports additional programming features that bear on call graph construction, like methods and anonymous functions. At a syntactic level, we can extend Comby to match method definitions, e.g.,

```
func ($v $t) $f(...) $r? {$body*}
```

Which matches Go method syntax like:

```
func (v Vertex) Abs() float64 {...}
```

We may continue to emit edge facts as-is for methods and ignore the receiver type \$t. Alternatively, we could extend the domain to distinguish calls via methods with a relation methodEdge("\$t", "\$f", "\$c"). Whether to extend these definitions will depend on the context of the practical application at hand. Notably, a declarative approach can ease tailoring fact generation to particular

applications, depending on context and language complexity. On the other hand, we recognize that languages may use syntax that is awkward to match. An attempt may even be fruitless for functional programs that make heavy use of function passing or partial application. In these cases, we envision that building on increasingly language-aware tooling³ can enable more precise (but still declarative) methods for generating facts. We observe that the benefit and tradeoff of our initial approach is that simple and lightweight specifications (like those of Fig. 5a) generalize well, if not precisely, to multiple imperative languages like Go, Java, C, and so on. This attribute is compelling where language-specific tooling is absent or overly complex for the purpose at hand, as we show in §3.

Extending semantic matching. Despite the tendency for languages like C to call functions directly, syntax alone is generally not indicative enough to precisely establish call relations. Consider the Go function in Fig. 6. Without knowing the context of imported packages and locally scoped variables, it is syntactically ambiguous whether dot accesses refer to local variables (like p) or imported packages (like fmt). More generally, complex analyses like pointer-analysis benefit from type information (Aho et al.) and language-specific semantics will influence the specificity of type constraints to generate facts.

```
import "fmt"

func main() {
   p := Printer{}
   p.Println("hello world")
   fmt.Println("hello world")
}
```

Figure 6

Due to language-specific semantics, we must appeal to tooling in e.g., compilers to resolve ambiguity. Recent advances use language servers (Niephaus et al., 2020) that expose semantic properties via an API. Our idea is to incorporate this semantic information via language servers, where declarative specification is *decoupled* from advanced, external processing that provides contextual semantic information. A prototype query that integrates Comby with the Go language server, for example, could allow conditionally emitting edge facts where the identifier refers to an imported package:⁴

```
where rewrite $body {
  $c(...) ->
     $c.type == "package",
     edge("$f", "$c").
}
```

3. Evaluation

Our evaluation considers the feasibility, accuracy, and speed of declaratively emitting call facts on large realworld projects written in three languages: Go, C, and Zig. We chose Go because it is a popular language with existing tooling to generate and visualize call graphs. This tooling provides a basis for a qualitative comparison in §3.1. We chose Zig because it is a relatively new language that further demonstrates the generality and speed of our declarative approach. To demonstrate the approach at scale, we run fact generation over the Linux kernel, which is written in C. We show that we can quickly and easily generate call graph relations without language-specific in tooling §3.2. All experiments were performed on a 6-core desktop machine (Core i5-9400F CPU, Ubuntu 20.04 LTS, 16GB RAM). All data and tooling is released toward Open Science and available at github.com/comby-tools/direct-to-datalog and archived by citable DOI 10.5281/zenodo.5520885.

3.1. Qualitative call graph comparison

We qualitatively compare our call graph output to that of go-callvis,⁵ a Go-specific tool. Our objective is to compare how well our syntactic approach recovers static call relations, and we use go-callvis output as ground truth. go-callvis fully parses Go code and qualifies functions and methods by package imports. Its final call graph representation is therefore richer than what our syntax-driven approach supports. Thus, we use go-callvis to qualify how well our approach approximates ground truth, not whether we can achieve tooling parity. Fundamentally, we are comparing how well the four-line specification in Fig. 5a approximates a relevant subset of call edges that result from language-specific tooling and libraries that span thousands of lines of code.

For a tractable qualitative comparison, we generate call graphs for the upgrade package in the syncthing Go project.⁶ The package comprises approximately 600 lines of Go code across 5 files. Fig. 7 visualizes the static calls found in our approach (left) versus go-callvis

³e.g., Tree-sitter, github.com/tree-sitter/tree-sitter.

⁴We use a convention of package to refer to a type in the type environment—a fully general solution relies on a server maintaining this state, and appropriate conventions to refer unambiguously to types.

⁵https://github.com/ofabry/go-callvis

⁶The upgrade package is the canonical example visualized in the go-callvis repository.

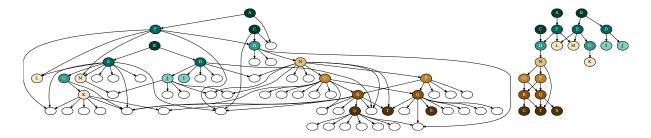


Figure 7: Two call graphs generated for the upgrade package in the syncthing Go project. Nodes correspond to functions, with shortened labels for visual comparison. On the left, the visual call graph for edges generated by the declarative specification in Fig. 5a (our approach). On the right, the static call graph generated by existing tool go-callvis starting at root functions in the same package. The takeaway is that our facts yield a subgraph that is isomorphic to the static call graph generated by the language-specific tool go-callvis (i.e., no edges are missed by our approach). Note: as a matter of design, go-callvis omits visualizing certain call sites by default (e.g., built-in functions like len). We do report these in our approach, which accounts for unlabeled nodes in the left graph.

output (right). To ease visual comparison, we show go-callvis output rooted at functions declared in the upgrade package, and do not render functions that call into the upgrade package from external packages. Note that our approach reports more nodes and edges because go-callvis, by design, omits certain functions in the Go standard library by default.⁷

The key result is that our approach yields a subgraph that is isomorphic to the go-callvis static call graph. That is, *no edges are missed* by our approach. This result supports the premise that succinct, declarative patterns can accurately generate facts to drive analyses, to, e.g., compute reachability properties over static call graphs.

3.2. Fact generation speed and generality

Table 1 demonstrates the speed of our approach on real-world repositories. To demonstrate generality of our approach we evaluate over large projects for Go and C, as well as projects for a trending language called Zig. Minimal changes are needed to adapt the Go pattern in Fig. 5a to work for static C and Zig calls. Due to Zig's C-like syntax, we only need to change the function keyword to match fn:

Similarly, we support C syntax with:

Table 1 shows that our approach is fast on very large projects. Fact generation for some of the largest Go

Lang	Project	KLOC	# Facts	# Funcs	Time
Go	Go	1,701	321,084	34,658	2m56s
	K8s	2,436	334,308	31,669	2m33s
	Sync	131	21,665	1,908	9s
Zig	Zig	467	70,461	7,414	42s
	ZLS	16	2,454	256	2s
	Dida	5	1,381	165	2s
С	Linux	20,916	3,660,511	513,264	39m14s

Table 1: Call graph fact generation over Go, Zig, and C projects. KLOC is the thousands of Lines of Code processed (1,000 KLOC is 1 million lines of code). #Facts is the number of static calls edges generated. #Funcs is the number of functions matched. In general, fact generation is fast and yields many static call relations across all languages.

projects finishes in under 3 minutes. At the extreme, we generate over 3.5 million facts over roughly 21 million lines of C code in 40 minutes for the Linux kernel. We successfully generate thousands of facts over all three languages. Interestingly, we observe a consistency in the ratio of call facts to functions: on average, across all projects, we generate 9.39 call facts per function (standard deviation ≈ 1.27). This is a promising positive indicator that our syntax patterns generate facts consistently across languages.⁸

4. Related Work

Pioneering work in declarative program analysis demonstrates efficient and succinct formulations using Datalog (Whaley et al.; Jordan et al., 2016; Bravenboer and Smaragdakis, 2009). Existing work focuses on deep,

⁷It is also possible to similarly tailor rules in Comby to omit output of such edges; we elide discussion for brevity.

⁸Dually, this observation raises the prospect of cross-language fact generation for "natural" software properties (Hindle et al., 2012).

language-specific properties and domains (e.g., pointer analysis for Java). These correspondingly implement language-specific frameworks and parsing routines to extract facts in the domain. None, to our knowledge, have attempted to generalize a declarative approach for fact generation across multiple languages, nor evaluate the feasibility of fact generation for cross-language properties like call graph construction. Alternative tools and frameworks exist for declaratively transforming syntax in multiple languages (Maletic and Collard, 2015; Cordy, 2006; Erdweg et al., 2013). We are not aware of any that attempt to fill the gap for declaratively generating Datalog facts. We used Comby (van Tonder and Le Goues, 2019) because it is simple, language-accessible, and fast; existing tools with similar properties may also implement the fact generation routines described in this article.

5. Conclusion

We presented the first approach that investigates the feasibility and appeal of an end-to-end declarative pipeline across multiple languages, where declarative code rewriting directly outputs Datalog facts. Our key result shows how we use this approach to generate thousands of static call edge facts across multiple languages (Go, C, and Zig) and that it scales to large, real world projects. The declarative specification requires less than 10 lines of code and can achieve a degree of qualitative parity with language-specific call graph tools implemented in hundreds of lines of imperative code (§ 3.1). Datalog engines like Soufflé directly consume facts generated by our approach and can then answer, e.g., call graph reachability properties. We envision that our syntax-driven approach can incorporate languagespecific semantic information (via Niephaus et al. (2020)) to expand analysis kinds and precision (e.g., pointer analysis) while retaining the benefits of declarative specification.

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