Profile-Guided Meta-Programming

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Abstract

Modern compilers such as GCC, .NET, and LLVM incorporate profile-guided optimizations (PGOs) on low-level intermediate code and basic blocks, with impressive results over purely static heuristics. Recent work shows that profile information is also useful for performing source-tosource optimizations via meta-programming. For example, using profiling information to inform decisions about data structures and algorithms can potentially lead to asymptotic improvements in performance. General-purpose metaprogramming systems should provide access to profile information so meta-programmers can write their own, potentially domain-specific optimizations. Existing profile-guided meta-program come with their own special-purpose toolkits, specific to a single optimization, creating barriers to use and development of new profile-guided meta-programs.

We propose an approach for supporting profile-guided meta-programs in a general-purpose meta-programming system. Our approach is parametric over the particular profiling technique and meta-programming system. We demonstrate our approach by implementing it in two different metaprogramming system: the syntactic extensions systems of Chez Scheme and Racket.

Introduction

Profile-guided optimization (PGO) is a compiler technique in which a compiler uses profile information, e.g., counts of how often each expression is executed, gathered from test runs on representative sets of inputs to generate more efficient code. The profile information acts as an oracle for runtime behavior, and informs low-level optimization decisions, e.g., decisions about reordering basic blocks, inlining, reordering conditional branches, and function layout in memory (Gupta et al. 2002). The resulting code usually exhibits improved performance, at least on the represented class of inputs, compared to code generated with static optimization heuristics. For example, using profiling information to inform inlining decisions in Java resulted in up to 59% improvement over static heuristics (Arnold et al. 2000). Modern compilers that support PGO include .NET, GCC, and LLVM (Lattner 2002).

Profile information has also proven useful to imple-Not sure if ment profile-guided meta-programs. Meta-programs, i.e., cite net programs that operate on programs, are used to imple-and gcc ment high-level abstractions such as efficient abstract li-documenbraries like Boost (Dawes and Abrahams 2009) and high-tation or performance domain specific languages (K. Sujeeth et al. not. 2014; Rompf and Odersky 2010). Using profile-guided meta-programming. Chen et al. (2006a) implement process placement for SMP clusters. Liu and Rus (2009) provide tools that use profile information to identify suboptimal usage of the STL in C++ source code. Languages with general-purpose meta-programming systems include C, C++, Haskell (Sheard and Peyton Jones 2002), Java (Erdweg et al. 2011), ML (Sheard and Jones 2002; Taha and Sheard 2000), Racket (Flatt and PLT 2010), Scheme (Dybvig et al. 1993), and Scala (Burmako 2013).

Existing general-purpose meta-programming systems do not provide profile information about the input programs on which meta-programs operate. Therefore, existing profileguided meta-programs introduce new special-purpose toolkits for profiling and meta-programming. Instead, generalpurpose meta-programming systems should provide access to profile information. Meta-programmers could then implement profile-guided meta-programs while reusing the metaprogramming and profiling tools of an existing, familiar, system. Programmers could then take advantage of all the metaprograms implemented in that system.

We propose an approach for supporting profile-guided meta-programming in a general-purpose meta-programming system. The approach provides a simple API through which meta-programs can access fine-grain source-level profile information, and does not interfere with traditional, i.e., "lowlevel" PGOs.

We implement this approach in Chez Scheme using stan-Say dard and efficient block-level profiling techniques (Ball and about R. Larus 1994; G Burger and Kent Dybvig 1998). We also profiling implement this approach in Racket (Flatt and PLT 2010) informa-

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tion being available run-time 2014/11/12 decisions, in later sections

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purely as a library, using pre-existing profiling and metaprogramming tools.

The remainder of the paper is organized as follows. In section 2, we present a running example and introduce Scheme-style meta-programming. In section 3, we present the design of our approach and an example of an API provided by a meta-programming system using our approach. In section 4, we present two instantiations of our approach, one in Chez Scheme and one in Racket. In section 5, we demonstrate that our approach is general enough to implement and extend existing PGOs and profile-guided meta-programs. In section 6, we related to existing work on PGOs and profile-guided meta-programming.

The main contributions of the paper are:

- · A general approach for profile-guided meta-programming.
- Two instantiations of our approach
- An evaluation of our approach based on implementing three existing profile-guided meta-programs.

2. A running example

We first introduce a Scheme syntax extension which we use as a running example and to familiarize readers with Scheme and Racket flavor meta-programming.

Figure 1: Example syntax extension

In figure 1, define-syntax introduces a new syntax extension if-r. Any uses of if-r in the source will be rewritten using the code in the body of the extension. For example, the function in figure 2 uses if-r. The extension will receive the argument:

This is a data representation of a term called a syntax object. The forms #', #', and #, implement Lisp's quote, quasiquote, and unquote but on syntax instead of lists. Together they give us a templating system for syntax. syntax-case performs pattern matching on syntax objects.

At compile time, if-r it looks up the profile information attached to each branch, reorders the branches based on which is more likely to be executed. It uses profile-query

Figure 2: Using if-r

to access the profile information for each branch and generate an if expression. This transformation is not a meaninful optimizaion and is only used for illustrative purposes. The syntax extension is expanded at compile-time, while the resulting if will be run at run-time.

3. Approach and API

This section presents the high-level design of our approach and presents a sketch of the API provided to meta-programmers. Our approach is not specific to a particular profile technique, but for simplicity our explinations refer to counter-based profile information.

3.1 Profile points

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To store and access profile information, we need to associate profile information with the source expressions on which meta-programs operate. *Profile points* uniquely identify expressions that should be profiled by the profiler. For instance, if two expressions are associated with the same profile point, then they both increment the same profile counter when executed. Conversely, if two expressions are associated with different source objects, then they increment different profile counters when executed.

For fine-grain profiling, each input expression and subexpression can have a unique profile point. In the case of our running example, separate profile points are associated with #'(if ...), #'(subject-contains email "PLDI"), #'subject-contains, #'email, #'"PLDI", #'(flag email 'spam), and so on. Note that #'flag and #'email appear multiple times, but each occurance can have a unique profile point.

In addition to profile points associated with input expressions, meta-programs can also manufacture new profile-points. Meta-programmers may want to profile generated expressions separately from any other expression in the source program.

The meta-programmer can access profile information by passing a profile points, or object with an associated profile point, to the API call profile-query seen in our running example.

Profile Information

Absolute profile information such as exact counts are incomparable across different data sets. Multiple data sets are important to ensure PGOs can optimize for multiple classes of inputs expected in production. Instead, our API provides profile weights. The profile weight of a profile point in a given data set is the ratio of the absolute profile information for that profile point to the maximum of all other profile point, represented as a number in the range [0,1]. In the case of counters, the profile weight for a given profile point is count for that point divided by the the count for the most frequently executed profile in the data set. This provides a single value identifying the relative importance of an expression and simplifies the combination of multiple profile data

TODO: Still want to say something about percent-ofaverage

To demonstrate profile weights, consider the running example from figure 2. Suppose in the first data set, (flag email 'important) runs 5 times and (flag email 'spam) percent-of-runs 10 times. In the second data set, (flag email 'important) runs 100 times and (flag email 'spam) run 10 times. Figure 3 shows the profile weights computed after percent-of- each data set.

```
;; After loading data from data set 1
(flag email 'important) \rightarrow 5/10
                                                  ;; 0.5
(flag email 'spam)
                           \rightarrow 10/10
                                                  ;; 1
;; After loading data from data sets 1 and 2
(flag email 'important) \rightarrow (.5 + 100/100)/2 ;; 0.75
(flag email 'spam)
                          \rightarrow (1 + 10/100)/2
                                                 ;; 0.55
```

Figure 3: Sample profile weight computations

Complete API sketch

Here we sketch the API.

To create profile points,

```
(make-profile-point)
```

generates profile points deterministically, to ensure profile information of generated profile points from previous runs is accessible.

To attach profile points to generated expressions,

```
(annotation-expr expr profile-point)
```

takes an expression, such as a syntax object, and a profile point, and associates the expression with the profile point.

To access profile information,

```
(profile-query expr)
```

takes an expression associated with a profile point, and returns the profile information associated with that profile point.

To store profile information a run,

```
(store-profile-info filename)
```

takes a filename and stores profile information from the profiling system to file.

To load profile information a run,

```
(load-profile-info filename)
```

takes a filename and loads profile information from the file so the its accessible by profile-query.

Implementations

In this section we describe the instantiations of our approach in Chez Scheme and in Racket, and briefly desc

4.1 Chez Scheme implementation

Chez Scheme implements exact counter based profiling. Adding a profile point for every single source expression requires care to instrument correctly and efficiently. As expressions optimizatiosn duplicate or throw out expressions, the profile points must not be duplicated or lost.

For every profile point Chez Scheme generates an expression (profile src), where src is the source object for that profile point, treats this profile expression as an effectful expression that must not be removed or duplicated. To instrument profiling efficiently, profile expressions are preserved until generating basic blocks. While generating basic blocks, all the source objects from the profile expressions can be attached to the basic block in which they appear. ¹ Using techniques from Burger and Dybvig (1998), we generate at most one counter per block, and fewer in practice.

Chez Scheme implements profile points using source objects (Dybvig et al. 1993) to uniquely identify profile points. Chez Scheme source objects contains a file name and starting and ending character positions. Source objects uniquely identify every source expression, providing fine-grain profile information. The Chez Scheme reader automatically creates and attaches these to each syntax object read from a file, using them, e.g., to give error messages in terms of source locations. Chez Scheme also provides an API to programmatically manipulate source objects and attach them to syntax (Dybvig 2011 Chapter 11).

We generate a new source objects by adding a suffix to the file name of a base source object. By basing generated source objects on source objects from the original source program, errors in generated code are easier to debug as the generated code contains source file information from the meta-program that generated the code. The meta-programming system's runtime maintains an associative map of source objects to profile weights which is updated by API calls. The API provide by Chez Scheme nearly identical to the one sketched in section 3.3.

4.1.1 Source and Block PGO

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One goal of our approach is to complement rather than interfere with traditional, e.g., basic block-level PGO, which Chez Scheme also supports. However, since meta-programs may generate different source code after optimization, the

¹ We reuse this infrastructure to profile basic blocks by generating a new profile point for each basic block.

low-level representation will change after meta-programs perform optimizations. Therefore we need to instrument and perform source and basic block-level optimizations separately. We describe a workflow for our approach via the running example from figure 2.

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To get both source-level and block-level optimizations, we first instrument the program for source profiling. After running it on representative inputs, we get the profile weights such as in figure 3. Next we recompile using that source profile information, and instrument profiling for basic blocks. The generated source code, figure 2, will remain stable as long as we continue to optimize using the source profile information. Since the generated source code remains stable, so do the generated basic blocks. Now we profile the basic blocks generated from the optimized source program. Finally, we use both the source profile information and the basic block profile information to do profile-guided optimizations via meta-programming and traditional low-level optimizations

4.2 Racket implementation

The Racket implementation uses a pre-existing Racket profiling implementation call errortrace. The errortrace library provides exact profile counters, like the Chez Scheme profiler.

The Racket implemention implements profile points by using source information attached to each syntax object. Racket attaches the file name, line number, etc to every syntax object, and provides functions for attaching source information when building a new syntax object. Our implementation provides wrappers to extract source information into separate source objects, and to merge source objects into Racket syntax objects. We then generate source objects in essentially the same way as in Chez Scheme.

We implement a library which provides a similar API to the one sketched in section 3.3. This library maintains the map from source objects to profile information and computers profile weights. This library is implemented as a standard Racket library that can be called by meta-programs, and requires no changes to either the Racket implementation or the errortrace library.

4.3 Instantiations in other meta-programming systems

Both of instantiations of our approach are in similar Schemestyle meta-programming systems, but the approach can work in any sufficiently expression meta-programming system.

Template Haskell (Sheard and Jones 2002), MetaML (Taha and Sheard 2000), MetaOCaml (Czarnecki et al. 2004), and Scala (Burmako 2013) all feature powerful meta-programming facilities similar to that of Scheme (Dybvig et al. 1993). They allow executing expressive programs at compiletime, provide direct access to input expressions, and provide template-style meta-programming facilities similar to Scheme. C++ template meta-programming is more restricted

than the above systems, so it is not clear how to instantiate our approach for C++ templates.

5. Case Studies

In this section we evaluate the generality of our approach by implementing existing profile-guided meta-programs in each of our instantiations of our approach. We first demonstrate optimizing Scheme's case, a multi-way branching construct similar to C's switch, as a meta-program. Then we then implement profile-guided receiver class prediction (Grove et al. 1995; Hölzle and Ungar 1994) for an object-oriented DSL. Finally we implement a sequence datatype that specializaes each instannce to a list or vector, based on profiling information, automating the recommendations performed by tools like Perflint (Liu and Rus 2009).

5.1 Profile-guided conditional branch optimization

As our first case study, we perform profile-guided conditional branch optimization for Scheme's case construct, which is similar C's switch statement. In C#, switch statements must be mutually exclusive and do not allow fall through; each case must end in a jump such as "break". The .NET compiler features profile-guided reordering switch statements to check the most common cases first. This case study shows that our approach can be used to easily implement this optimization.

The case construct takes an expression key-expr and an arbitrary number of clauses, followed by an optional else clause. The left-hand side of each clause is a list of constants. case executes the right-hand side of the first clause in which key-expr is equal? to some element of the left-hand. For simplicity, we assume the left-hand sides are mutually exclusive and ignore the else clause². Figure 4 shows an example case expression.

```
(define (parse stream)
  (case (peek-char stream)
  [(#\space #\tab) (white-space stream)]
  [(0 1 2 3 4 5 6 7 8 9) (digit stream)]
  [(#\() (start-paren stream)]
  [(#\()) (end-paren stream)]
  ...))
```

Figure 4: An example using case

Figure 5 shows the profile-guided implementation of case that tries the most executed clauses first. First it parses each clause into a struct containing the list of keys from the left-hand side, and the expressions from the right-hand side. Then it generates an invocation of another meta-program, exclusive-cond, which reorders its branches based on profile information. The full implementation of case is 41-line.

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² The full implementation handles the full generality of Scheme's case

```
(define-syntax (case syn)
(struct case-clause (keys body))
(define (parse-clause clause)
  (syntax-case clause ()
   [((k ...) e1 e2 ...)
    (make-case-clause #'(k ...) #'(e1 e2 ...) (profile-query #'e1))]))
(syntax-case syn ()
  [(_ key-expr clause ...)
    ; Evaluate the key-expr only once, instead of
     copying the entire expression in the template.
  #'(let ([t #,key-expr])
       (exclusive-cond
        ; Parse clauses and splice a list of generated tests
         into exclusive-cond
       #,@(for/list ([clause (map parse-clause #'(clause ...))])
           ; Transform each case clause into branch that tests if the
            key expression, t, is in the list of keys for the clause
          #'((in-list? t '#, (case-clause-keys clause))
              #,@(case-clause-body clause))))))))
```

Figure 5: Implementation of case

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Figure 6, introduces the exclusive-cond construct, a multi-way conditional branch, like Lisp's cond³, but expects all branches to be mutually exclusive. Because the branches are mutually exclusive we can safely reorder the clauses to execute the most likely clauses first. exclusive-cond simplifies the implementation of case, and demonstrates an important feature of profile-guided meta-programming—meta-programming allows the programmer to encode their knowledge, e.g., that the branches of this conditional are mutually exclusive, in their program and take advantage of optimizations that would have otherwise been impossible.

First the implementation of exclusive-cond parses each clause into a struct that contains the original clause and the profile information. Then it sorts the clauses by weight and generates a regular cond. The full implementation of exclusive-cond is 24-line.

Figure 7 shows the code generated from the example case expression from figure 4

5.2 Profile-guided receiver class prediction

We provide a meta-program that implements profile-guided receiver class prediction (Grove et al. 1995; Hölzle and Ungar 1994) for a simplified object system implemented as a syntax extension. This case study demonstrates that our mechanism is both general enough to implement well-known profile-guided optimizations, and powerful enough to provide DSL writers with standard PGOs.

Figure 8 shows the key parts of the implementation of recevier class prediction. A method call such as (method shape area) is actually a meta-program that generates code as follows. First, it generates a new source object for each

```
; After case expands
(define (parse stream)
(let ([t (peek-char stream)])
   (exclusive-cond
     [(in-list? t '(#\space #\tab))
      (white-space stream)]
     [(in-list? t (0 1 2 3 4 5 6 7 8 9)) (digit stream)]
     [(in-list? t (#\()) (start-paren stream)]
     [(in-list? t (#\))) (end-paren stream)])))
: After exclusive-cond expands
(define (parse stream)
(let ([t (peek-char stream)])
   (cond
     [(in-list? t '(#\space #\tab))
      (white-space stream)]; Run 55 times
     [(in-list? t (#\())
      (start-paren stream)]; Run 23 times
     [(in-list? t (#\)))
      (end-paren stream)]
                            ; Run 23 times
     [(in-list? t (0 1 2 3 4 5 6 7 8 9))
      (digit stream)]
                            ; Run 10 times)))
```

Figure 7: Generated code from figure 4

class in the system. Then for each of these newly generated source objects, it instruments a call to the dynamic dispatch routine. When profile data is not available, the implemation generates a cond expression which tests the class of the object and calls the dynamic dispatch routine, but with a different profile point for each branch.⁴ That is, method call site is instrumented by generating a multi-way branch to the same dynamic dispatch routine, but with separate profile points in each branch. When profiling information is

³ The full implementation handles other **cond** syntaxes and **else** clauses.

⁴ A production implementation would create a table of instrumented dynamic dispatch calls and dynamically dispatch through this table, instead of instrumenting code with **cond**, but this complicates vizualizing ths instrumentation.

```
(define-syntax (exclusive-cond syn)
  (struct clause (syn weight))
  (define (parse-clause clause)
    (syntax-case clause ()
      [(test e1 e2 ...) (make-clause clause (profile-query #'e1))]))
  (define (sort-clauses clause*)
    (sort > #:key clause-weight (map parse-clause clause*)))
  (syntax-case x (else)
    [(_ clause ...)
    #'(cond #,@(map clause-syn (sort-clauses #'(clause ...))))]))
```

Figure 6: Implementation of exclusive-cond

available, we expand into a cond expression that tests for the most frequently used classes at this method call site, and inlines thost methods—that is, we perform polymorphic inline caching using the profile information. Otherwise we fall back to dynamic dispatch. The full implementation of profile-guided receiver class prediction is 44-line of code. The rest of the DSL implementation is an additional 82-line.

Figure 9 shows an example method call, the resulting code after instrumentation, and the resulting code after optihash table mization. Note that the each occurences of (instrumenteddispatch x area) has a different source objects, so they are each profiled separately.

> We have demonstrated that our approach can easily implement a well known profile-guided optimization as a meta-program. As a further improvement, we could reuse exclusive-cond to test for the most likely class first.

5.3 Data Structure Specialization

So far we've demonstrated that our technique support traditional profile-guided optmizations via meta-programming. However, meta-programs have access to high-level information such as different algorithms or data structures might be cause an asymptotic speed up (Liu and Rus 2009). In this case study we show our approach is general enough to implement this kind of profiling tool, and even go beyond it by automating the recommendations.

We provide implementations of lists and vectors⁵ that warn the programmer when a different representation may lead to asymptotic performance gains. The implementations provide wrappers around the standard list and vector functions, using newly generated source objects to separately profile the uses of each instance of the data structures. Finally, we provide an implementation of a sequence datatype that will automatically specialize to a list or vector based on profiling information. As this is done via a library, the programmer can easily opt-in to such automated high-level changes without changing their code.

```
(class Square
  ((length 0))
  (define-method (area this)
    (sqr (field this length))))
(class Circle
  ((radius 0))
  (define-method (area this)
    (* pi (sqr (field this radius)))))
(class Triangle
  ((base 0) (height 0))
  (define-method (area this)
    (* 1/2 base height)))
(for/list ([s (list cir1 cir2 cir3 sqr1)])
  (method s area))
; After instrumentation
(let* ([x c])
  (cond
    [(class-equal? x 'Square)
                                 ; Run 1 time
     (instrumented-dispatch x area) 1
    [(class-equal? x 'Circle)
                                 ; Run 3 times
     (instrumented-dispatch x area)]
    [(class-equal? x 'Triangle) ; Run 0 times
     (instrumented-dispatch x area)]
    [else (dynamic-dispatch x area)]))
; After optimization
(let* ([x c])
    [(class-equal? x 'Square) ; Run 1 time
     (let ([this x]) (sqr (field x length)))]
    [(class-equal? x 'Circle) ; Run 3 times
     (let ([this x]) (* pi (sqr (field x radius))))]
    [else (dynamic-dispatch x area)]))
```

Figure 9: Example of profile-guided receiver class prediction

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TODO: Maybe implement the instrumented later

⁵ Vectors are essentially arrays in Scheme.

```
(define-syntax (method syn)
  (syntax-case syn ()
    [(_ obj m val* ...)
     ; Don't copy the object expression throughout the template.
    #'(let* ([x obj])
         (cond
           #,@(if no-profile-data?
                  ; If no profile data, instrument!
                  (for/list ([d instr-dispatch-calls] [class all-classes])
                    #'((class-equal? x #, class) (#, d x)))
                  ; If profile data, inline up the top inline-limit classes
                  ; with non-zero weights
                  (for/list ([class (take sorted-classes inline-limit)])
                    #'((class-equal? x #, class)
                       #, (inline-method class #'x #'m #'(val* ...))))
           ; Fall back to dynamic dispatch
           [else (dynamic-dispatch x m val* ...)]))])
```

Figure 8: Implementation of profile-guided receiver class prediction

```
(struct list-rep (instr-op-table ls))
(define-syntax (profiled-list syn)
   ; Create fresh source objects.
    ; Use list-src to profiles operations that are asymptotically fast on lists
    ; Use vector-src profiles operations that are asymptotically fast on vectors
    (define list-src (make-source-obj syn))
    (define vector-src (make-source-obj syn))
    (syntax-case syn ()
      [(_ init-vals ...)
       (unless (>= (profile-query list-src) (profile-query vector-src))
         ; Prints at compile time.
         (printf "WARNING: You should probably reimplement this list as a vector: ~a\n" x))
       #'(make-list-rep
          ; Build hash table of instrumented calls to list operations
           ; The table maps the operation name to a profiled call to the
           : built-in operation.
           (let ([ht (make-eq-hashtable)])
             (hashtable-set! ht 'car #, (instrument-call car list-src))
            ht)
           (list init* ...))]))
```

Figure 11: Implementation of profiled list

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Figure 11 shows the implementation of the profiled list constructor. This constructor has the same interface as the standard Scheme list constructor—it takes an arbitrary number of elements and returns a representation of a linked list. The representation of a profiled-list is a pair of the underlying linked list and a hash table of profiled operations. That is, each instance of a profiled-list contains a table of profiled calls to the underlying list operations. The profiled list constructor generates these profiled operations by simply wrapping the underlying list operations with the appropriate source object source objects. It generates two source objects for each list. One is used to profile operations that are asymptotically fast for lists and the other is used to profile

operations that are asymptotically fast for vectors. Finally, the library exports new versions of the list operations that work on profiled list representation. For instance, it exports car, which a profiled-list, and uses the profiled call car from the hash table of the profiled list on the underlying list. When profiling information already exists, for instance, after a profiled run, this list constructor emits a warning (at compile time) if the list fast vector operations are more common than fast list operations.

We also provide an analogous implementation of vectors. Our technique would also scale to the other data structures analyzed by Perflint. Because our meta programs are integrated into the language, rather than existing as a separate

```
; After optimization
(let* ([x c])
  (exclusive-cond
    [(class-equal? x 'Square) ; Run 1 time
     (let ([this x]) (sqr (field x length)))]
    [(class-equal? x 'Circle); Run 3 times
     (let ([this x]) (* pi (sqr (field x radius))))]
    [else (dynamic-dispatch x area)]))
; After more optimization
(let* ([x c])
  (cond
    [(class-equal? x 'Circle); Run 3 times
     (let ([this x]) (* pi (sqr (field x radius))))]
    [(class-equal? x 'Square)
                              ; Run 1 time
     (let ([this x]) (sqr (field x length)))]
    [else (dynamic-dispatch x area)]))
```

Figure 10: Profile-guided recevier class prediction, sorted.

tool in front of the compiler, we can provide libraries to the programmer that automatically follows these recommendations rather than asking the programmer to change their code. To demonstrate this, we implement a profiled sequence datatype that will automatically specialize to a list or vector, at compile time, based on profile information.

Figure 12 shows the implementation of the profiled sequence constructor. The code follows the same pattern as the profiled list. The key difference is we conditionally generate wrapped versions of the list or vector operations, and represent the underlying data using a list or vector, depending on the profile information.

Related Work

TODO:

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to all

Add links

references.

Profile-guided optimizations

first magness Modern systems such as GCC, .NET, and LLVM (Lattner 2002) use profile directed optimizations. These systems uses profile information to guide decisions about code positioning, register allocation, inlining, and branch optimizations.

> GCC profiles at the level of an internal control-flow graph (CFG). To maintain a consistent CFGs across instrumented and optimizated builds, GCC requires similar optimization decisions across builds (Chen et al. 2010). In addition to the common optimizations noted previously, .NET extends their profiling system to probe values in switch statements. They can use this value information to optimize switch branches, similar to the implementation of case we presented in section 5.1.

> LLVM has a different model for PGO. LLVM uses a runtime reoptimizer that monitors the running program. The runtime can profile the program as it runs "in the field" and perform simple optimizations to the machine code, or call to

an offline optimizer for more complex optimizations on the LLVM bytecode.

Recent work is still finding novel uses for profile information. Furr et al. (2009) present a system for inferring types in dynamic languages to assist in debugging. Chen et al. (2006b) use profile information to reorganize the heap and optimize garbage collection. Luk et al. (2002) use profile information to guide data prefetching. Debray and Evans (2002) use profile information to compress infrequently executed code on memory constrained systems.

6.2 Meta-program optimizations

Meta-programming combines the ability to provide high levels of abstraction while producing efficient code. Metaprogramming has been widely used to implement high performance DSLs (K. Sujeeth et al. 2013; K. Sujeeth et al. 2014; Rompf and Odersky 2010), whole general purpose languages (Barzilay and Clements 2005; Rafkind and Flatt 2012; Tobin-Hochstadt and Felleisen 2008), and productionquality compiler generators (W. Keep and Kent Dybvig 2013). Tobin-Hochstadt et al. (2011) implement the optimizer for the Typed Racket language as a meta-program. The HERMIT toolkit provides an API for performing program transformations on Haskell intermediate code before compiling, even allowing interactive experimentation (Farmer et al. 2012). Hawkins et al. (2012) implement a compiler for a language that generates C++ implementations of data structures based on high-level specifications.

Previous works integrates profiling to guide meta-program optimizations. Chen et al. (2006a) use profile-guided metaprogramming for performing process placement for SMP clusters. Šimunić et al. (2000) use profile-guided metaprograming to optimize the energy usage of embedded programs. Karuri et al. (2005) use fine-grained source profile information to optimize ASIP designs.

However, existing work introduce new toolkits for profiling and meta-programming. We provide a single, generalpurpose mechanism in which we can implement new languages, DSLs, abstract libraries, and arbitrary meta-programs, all taking advantage of profile-guided optimizations. Further, our approach reuses existing meta-programming and profiling facilities, rather than implementing new tools that interface the compiler in ad-hoc ways.

7. Conclusion

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Meta-programming is being used to implement high-level optimizations, generate code from high-level specifications, and create DSLs. Each of these can take advantage of PGO to optimize before information is lost or constraints are imposed. Until now, such optimizations have been implemented via toolchains designed for a specific meta-program or optimization. We have described a general mechanism for implementing arbitrary profile-guided meta-program optimizations, and demonstrated its use by implementing several

Figure 12: Implementation of profiled sequence

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optimizations previously implemented in seperate, specialized toolchains.

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