Profile-guided meta-program optimization

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Abstract

Many contemporary compilers allow the use of profile information to guide various low-level optimizations. This is not the case for contemporary meta-programming systems, although profile information can have an even greater impact on the high-level optimizations performed by meta-programs. For example, a meta-program sometimes has control over the data structures and algorithms used by the generated code, and use of profiling information to select appropriate data structures and algorithms can potentially lead even to asymptotic improvements in performance.

This paper describes a mechanism for supporting profile-guided meta-program optimization. It makes profile information available at the granularity of arbitrary target-language source points identified by the meta-program, while making use of standard and efficient block-level profile-instrumentation techniques. We have implemented the mechanism as part of Chez Scheme, with profile information made available via the syntactic abstraction facility through which Scheme supports meta-programming. The mechanism can be adapted to most meta-programming systems with compilers that support profiling.

1. Introduction

Meta-programs, or programs that write other programs, are often used to implement high-level abstractions ranging from simple syntactic abstractions, to compiler generators, to domain-specific languages (DSLs). To name a few, C, C++, Haskell, Scheme, ML, and Scala have support for meta-programming [2, 5, 7, 8, 16, 17]. Ideally, meta-programs would not be concerned with generating optimized code but instead leave that to the target-language compiler. However, information is sometimes lost or obscured during the translation into the target-language program. For example, constraints on types, ranges, and effects can be lost, as can the lack of constraints on data representation, algorithms, and evaluation order. Optimizations that depend on the lost information cannot be performed by the target-language compiler and thus must be performed by the meta-program, if at all.

Profile-guided optimization (PGO) is a compiler technique that uses data gathered at run-time on representative inputs to recompile and generate optimized code. The code generated by this recompilation usually exhibits improved performance on that class of inputs than the code generate with static optimization heuristics. For instance, a compiler can decide which loops to focus on unrolling based on which loops are executed more frequently. Many compilers such as .NET, GCC, and LLVM use profile-guided optimizations. The profile information used by these compilers, such as execution counts of basic blocks or control flow graph nodes, is low-level compared to the source-language operated on by meta-programs. So the optimizations that use the profile information are also performed on low-level constructs. Common optimizations include reordering basic blocks, inlining decisions, conditional branch optimization, and function layout decisions.

Many compiler optimizations can benefit from the availability of profile information and many contemporary compilers provide support for gathering and using profile information for this purpose. Profile information can have an even greater impact on meta-program optimizations. For example, a meta-program might select data structures and algorithms based on the frequency with which certain operations are performed, potentially even leading to improvements in asymptotic performance.

Existing techniques that use profile information for these kinds of meta-program optimizations introduce a custom toolchain, or expect the programmer to optimize code by hand. Chen et. al. implement their own profile and meta-program toolchain to provide a profile-guided meta-program for performing process placement for SMP clusters [9]. Liu and Rus provide a toolset that uses profile information find suboptimial usage of the C++ STL, but leaves it up to the programmer to make these changes [10]. Hawkins et. al. implement a compiler that generates C++ implementations of data structures based on high-level specifications [13, 14]. These works implement highly specific meta-programming or profiling systems to provide very advanced optimizations. Yet no general-purpose mechanism has been proposed to date that makes profile information available to meta-programs for these kinds of optimizations.

This paper describes such a mechanism. The mechanism makes profile information available at the granularity of arbitrary target-language source points identified by the meta-program. In the case of a meta-program implementing an embedded DSL, these could correspond to source expressions already present in the source-language program. In a manner similar to standard profile-guided optimization mechanisms, making use of this mechanism involves running the meta-program and compiler once to instrument the code, running the resulting executable one or more times on representative data to gather profile data, and running the meta-program and compiler a second time to generate the optimized code. During the second run of the meta-program, the meta-program retrieves the profile information associated with source points. The profile information is also available to the target-language compiler to support the optimizations it performs. The mechanism uses standard and efficient block-level profiling techniques and is potentially suitable for dynamic optimization of a running program in systems that support dynamic recompilation [1]. It enables using data sets from multiple executions of the instrumented program, and works with traditional (“low-level”) PGO.

This mechanism has been implemented as part of a high performance Scheme system, with profile information made available via an API accessible from the high-level syntactic abstraction facility through which Scheme supports meta-programming. It would be straightforward to adapt to most meta-programming systems with compilers that already support profiling.

The reminder of the paper is organized as follows. Section 2 presents the design of our system at a high level. Section 3 demonstrates how to use our mechanism to implement several optimizations as meta-programs. These example demonstrate how our work can be used to implement and build on past work in a single, general system. In particular, we show our work could be used to automate the recommendataions produced by Liu and Rus by automatically specialize an abstract sequence datatype [10]. We also demonstrate how to implement profile-guided receiver class prediction using our mechanism [6]. Section 4 discusses our implementation and how it works with traditional PGOs.

2. Design

This section presents the essential points of our system. We first discuss how source points are identified and manufactured. We then discuss how we store profile information and handle multiple data sets. We elide implementation particulars until section 4.

2.1 Source objcets

To perform arbitrary meta-program optimizations, we require profile information from arbitrary points in the source program. We model this using source objects, which act as unique keys to how often a particular point in the code is reached. Each source expression of a program is annotated with a unique source object. We can create new (fresh) source objects using `(make-source-object)`, and can create a new profile point by using `(profile src)`, where `src` is some source object. We access the profile information through the function `profile-query-weight`, which takes a source object and returns a number representing the execution frequency.

2.2 Profile weight

Instead of exact counts, we store execution counts relative to the most frequently executed expression in the program. This provides a single value that represents the relative importance of an expression and supports using multiple profile data sets. These profile weights are associated with each source object, and returned by `profile-query-weight`.

We considered comparing to the total number of expressions executed and the average number of times an expression is executed. In both cases, the results are distorted when there are a large number of expressions that are executed infrequently. In that case, a main loop might look infrequently executed if there are many start up or shut down steps. By comparing to the most expensive expression, we have a relatively stable comparison of how expensive some expression is, even in cases with many unused expressions or a few very expensive expressions.

To understand how we handle profile weights, consider a program with two loops, `A` and `B`. If `A` is executed 5 times, and `B` is executed 10 times, we store `(profile-query-weight A) = 5/10 = 0.5` and `(profile-query-weight B) = 10/10 = 1`. To support multiple data sets, we simple compute the average of these weights. For instance, if in a second data set `A` is executed 100 times and `B` is executed 10 times, then `(profile-query-weight A) = ((5/10) + (100/100))/2 = 0.75` and `(profile-query-weight B) = ((10/10) + (10/100))/2 = 0.55`. [1] Multiple data sets enable reuse and help the developer collect representative profile data. This is important to ensure our PGOs optimize for the class of inputs we expect in production.

[1] TODO: Diagram

3. Examples

This section demonstrates how our to use our mechanism, and how it generalizes and advances past work on profile-guided meta-programs. The first example demonstrates profile-guided receiver class prediction for a object-oriented DSL based on profile information. The final example demonstrates specializing a data structure based on profile information.

3.1 Scheme macro primer

```
; defines a macro (meta-program)
(define-syntax (do-n-times stx)
  ; pattern matches on the inputs syntax
  (syntax-case stx ()
    ; Example:
    ; (do-n-times 5 (display "*")) => *****
    [(do-n-times n body ...)
    ; #' creates a piece of syntax
     #'(let loop [(i n)]  ; the syntax 'n',
taken as input, is copied
              (if (zero? i)
                  (void)
                  (begin body ... (loop (sub1 i)))))]))
```

Figure 1: Sample macro

`#'`, `` #` ``, and `#,` implement Lisp's quote, quasiquote, and unquote but on syntax instead of lists. [2]

3.2 Profile-guided receiver class prediction

In this example we demonstrate how to implement profile-guided receiver class prediction [6] for a hypothetical object-oriented DSL with virtual methods, similar to C++. We perform this optimization through a general meta-program called `exclusive-cond`, a branching construct that can automatically reorder the clauses based on which is mostly likely to be executed.

[3] Consider a class with a virtual method `get_x`, called `Point`. `CartesianPoint` and `PolarPoint` inherit `Point` and implement the virtual `get_x`. We will use `exclusive-cond` to inline virtual method calls.
[4]

`cond` is a Scheme branching construct analogous to a series of if/else if statements. The clauses of `cond` are executed in order until the left-hand side of a clause is true. If there is an `else` clause, the right-hand side of the `else` clause is taken only if no other clause's left-hand side is true.

Figure 2 shows an example of a `cond` generated by our hypothetical OO DSL. The DSL compiler simply expands every virtual method call into a conditional branch for known instances of an object.

By profiling the branches of the `cond`, we can sort the clauses in order of most likely to succeed, or even drop clauses that occur too infrequently inline. However, `cond` is order dependent. While the programmer can see the clauses are mutually exclusive, the compiler cannot prove this in general and cannot reorder the clauses.

[2] TODO: expand, fix tt

[3] TODO: Use example from grove95; it's simpler

[4] TODO: borrowed from http://courses.engr.illinois.edu/cs421/sp2011/project/self-type-feedback.pdf

```
(cond
 [(class-equal? obj CartesianPoint)
  (field obj x)]
 [(class-equal? obj PolarPoint)
  (* (field obj rho) (cos (field obj theta)))]
 [else (method obj "get_x")])
```

Figure 2: An example of `cond`

Instead of wishing our compiler was more clever, we use meta-programming to take advantage of this high-level knowledge. We define `exclusive-cond`, figure 3, with the same syntax and semantics of `cond` [5], but with the restriction that clause order is not guaranteed. We then use profile information to reorder the clauses.

The `exclusive-cond` macro will rearrange clauses based on the profiling information of the right-hand sides. Since the left-hand sides will be executed depending on the order of the clauses, profiling information from the left-hand side is not enough to determine which clause is true most often.[6] The clause record stores the original syntax for the clause and the weighted profile count for that clause. Since a valid `exclusive-cond` clause is also a valid `cond` clause, the syntax is simply copied, and a new `cond` is generated with the clauses sorted according to profile weights. If an `else` clause exists then it is emitted as the final clause.

```
(exclusive-cond
  [(class-equal? obj CartesianPoint)
   ; executed 2 times
   (field obj x)]
  [(class-equal? obj PolarPoint)
   ; executed 5 times
   (* (field obj rho) (cos (field obj theta)))]
  [else (method obj "get_x")])

(cond
  [(class-equal? obj PolarPoint)
   (* (field obj rho) (cos (field obj theta)))]
  [(class-equal? obj CartesianPoint)
   (field obj x)]
  [else (method obj "get_x")])
```

Figure 4: An example of `exclusive-cond` and its expansion

Figure 4 shows an example of `exclusive-cond` and the code to which it expands. In this example, we assume the object is a `PolarPoint` most of the time.

3.2.1 `case`: Another use of exclusive-cond

`case` is a pattern matching construct, similar to C's `switch`, that is easily given profile directed optimization by implementing it in terms of `exclusive-cond`. `case` 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 `eqv?` to some element of the left-hand. If `key-expr` is not `eqv?` to any element of any left-hand side and an `else` clause exists then the right-hand side of the `else` clause is executed.

[5] We omit the alternative cond syntaxes for brevity.

[6] Schemers will note this means we cannot handle the single expression cond clause syntax.

```
(case x
  [(1 2 3) e1]
  [(3 4 5) e2]
  [else e3])
```

Figure 5: An example of a `case` expression

Figure 5 shows an example `case` expression. If `x` is 1, 2, or 3, then `e1` is executed. If `x` is 4 or 5, then `e2` is executed. Note that while 3 appears in the second clause, if `x` is 3 then `e1` will be evaluated. The first occurrence always take precedence.

Since `case` permits clauses to have overlapping elements and uses order to determine which branch to take, we must remove overlapping elements before clauses can be reordered. Each clause is parsed into the set of left-hand side keys and right-hand side bodies. Overlapping keys are removed by keeping only the first instance of each key when processing the clauses in the original order. After removing overlapping keys, an `exclusive-cond` is generated.

```
(exclusive-cond x
  [(memv x (1 2 3)) e1]
  [(memv x (4 5)) e2]
  [else e3])
```

Figure 6: The expansion of figure 5

Figure 6 shows how the example `case` expression from figure 5 expands into `exclusive-cond`. Note the duplicate 3 in the second clause is dropped to preserve ordering constraints from `case`.

3.3 Data type Selection

The previous examples show that we can easily bring well-known optimizations up to the meta-level, enabling the DSL writer to take advantage of traditional profile directed optimizations. While profile directed meta-programming enables such traditional optimizations, it also enables higher level decisions normally done by the programmer.

In this example we present a library that provides a sequence datatype. We consider this in the context of a DSL or library writer whose users are domain experts, but not computer scientists. While a domain expert writing a program my know they need a sequence for their program, they may not have the knowledge to figure out if they should use a tree, or a list, or a vector. Past work has bridge this gap in knowledge by providing tools that can recommend changes and provide feedback [7]. We take this a step further and provide a library that will automatically specialize the data structure based on usage.

The example in figure 7 chooses between a list and a vector using profile information. If the program uses `seq-set!` and `seq-ref` operations more often than `seq-map` and `seq-first`, then the sequence is implemented using a `vector`, otherwise using a `list`.

Figure 8 demonstrates the usage of the `define-sequence-datatype` macro. In this example, a sequence named `seq1` is defined and initialized to contain elements `0`, `3`, `2`, and `5`.

The macro expands into a series of definitions for each sequence operations and a definition for the sequence datatype. This example redefines the operations for each new sequence, creating fresh

[7] TODO: http://dx.doi.org/10.1109/CGO.2009.36

```
(define-syntax exclusive-cond
  (lambda (x)
    (define-record-type clause (fields syn weight))
    (define (parse-clause clause)
      (syntax-case clause ()
        [(e0 e1 e2 ...) (make-clause clause (or (profile-query-weight #'e1) 0))]
        [_ (syntax-error clause "invalid clause")]))
    (define (sort-clauses clause*)
      (sort (lambda (cl1 cl2)
              (> (clause-weight cl1) (clause-weight cl2)))
       (map parse-clause clause*)))
    (define (reorder-cond clause* els)
      #`(cond
          #,@(map clause-syn (sort-clauses clause*))
          #,@(if els #`(,els) #'())))
    (syntax-case x (else)
      [(_ m1 ... (else e1 e2 ...)) (reorder-cond #'(m1 ...) #'(else e1 e2 ...))]
      [(_ m1 ...) (reorder-cond #'(m1 ...) #f)])))
```

Figure 3: Implementation of `exclusive-cond`

```
(define-syntax define-sequence-datatype
   (lambda (x)
      ; Create fresh source object. list-src profiles operations that are
      ; fast on lists, and vector-src profiles operations that are fast on
      ; vectors.
      (define list-src (make-source-obj))
      (define vector-src (make-source-obj))
      ; Defines all the sequences operations, giving implementations for
      ; lists and vectors.
      (define op*
        `((make-seq ,#'list ,#'vector)
          (seq? ,#'list? ,#'vector?)
          ; Wrap the operations we care about with a profile form
          (seq-map ,#`(lambda (f ls) (profile #,list-src) (map f ls))
                   ,#`(lambda (f ls) (profile #,list-src) (vector-map f ls)))
          (seq-first ,#'first ,#'(lambda (x) (vector-ref x 0)))
          (seq-ref ,#`(lambda (ls n) (profile #,vector-src) (list-ref ls n))
                   ,#`(lambda (v n) (profile #,vector-src (vector-ref v n))))
          (seq-set! ,#`(lambda (ls n obj)
                         (profile #,vector-src) (set-car! (list-tail ls n) obj)
                    ,#`(lambda (v n obj)
                         (profile #,vector-src) (vector-set! v n obj))))))
        ; Default to list; switch to vector when profile information
        ; suggests we should.
        (define (choose-op name)
          ((if (> (profile-query-weight vector-src)
                  (profile-query-weight list-src))
              third
              second)
           (assq name op*)))
      (syntax-case x ()
        [(_ var (init* ...))
         ; Create lists of syntax for operation names and definitions
         (with-syntax ([(name* ...) (map first op*)]
                       [(def* ...) (map choose (map first op*))])
           ; and generate them
           #`(begin (define name* def*) ...
           ; Finally, bind the sequence.
                    (define var (#,(choose 'make-seq) init* ...))))])))
```

Figure 7: Implementation of `define-sequence-datatype`

```
(define-sequence-datatype seq1 (0 3 2 5))
```

Figure 8: Use of the define-sequence-datatype macro

source objects and new profiled operations for each seperate sequence. This ensures each instance of a sequence is profiled seperately.

4. Implementation

This section describes our implementation of the profiling system, and how source-level and block-level profile directed optimizations can work together in our system. First we present how code is instrumented to collect profile information. Then we present how profile information is stored and accessed. Finally we present how we use both source-level and block-level profile directed optimizations in the same system.

4.1 Source + block profiling

[8] When designing our source level profiling system, we aimed to take advantage of prior work on low level profile directed optimizations [9]. However, optimizations based on source-level profile information may result in a different set of blocks than the blocks generated for the profiled run of a program. If blocks are profiled for instance, by assigning each block a number in the order in which the blocks are generated, then the block numbers will not be consistent after optimizing with source information. Therefore optimization using source profile information and those using block profile information cannot be done after a single profiled run of a program.

We take the [10] naive approach to block profiling and use the following workflow to take advantage of both source and block leve profile directed optimizations. First we compile and instrument a program to collect source-level information. We run this program and collect only source-level information. Next we recompile and optimize the program using the source-level information only, and instrument the program to collect block-level information. The profile directed meta-programs reoptimize at this point. We run this program and collect only the block-level information. Finally, we recompile the program with both source-level and block-level information. Since the source information has not changed, the meta-programs generate the same source code, and thus the compiler generates the same blocks. The blocks are then optimized with the correct profile information.

While the workflow seems to significantly complicate the compilation process, the different between using only block-level profiling and using both source-level and block-level profiling is small. To use any kind of profile directed optimizations requires a 300% increase in the number of steps (from compile to compile-profile-compile). To use both source-level and block-level profile directed optimizations requires only an additional 66% increase in number of steps (compile-profile-compile to compile-profile-compile-profile-compile).

[11] We represent profile information as a floating point number between 0 and 1. Profile information is not stored as exact counts, but as execution frequency with respect to the most executed expression (refered to as 'percent of max'). If an expression `e1` is executed 1 time, and the most frequently executed expression `e10` is executed 10 times, then `(profile-query-weight e1)` returns .1, while `(profile-query-weight e10)` returns 1.

[8] TODO: Move this

[9] TODO: cite

[10] TODO: Not naive

[11] TODO: Fix up, reorganize

4.2 Instrumenting code

The naive method for instrumenting code to collect source profile information is to attach the source information to each AST node internally. At an appropriately low level, that source information can be used to generate code that increments profile counters. However this method can easily distort the profile counts. As nodes are duplicated or thrown out during optimizations, the source information is also duplicated or lost.

Instead we create a separate profile form that is created during macro expansion. Each expression `e` that has source information attached is expanded internally to `(begin (profile src) e)`, where `src` is the source object attached to `e`. The profile form is consider an effectful expression internally and should never be thrown out or duplicated, even if `e` is. [12] [13]

These profile forms are retained until basic blocks are generated. While generating basic blocks, the source objects from the profile forms are gathered up and attached to the basic block in which they appear. When a basic-block is entered, every instruction in that block will be executed, so any profile counters in the block must be incremented. Since all the profile counters must be incremented, it is safe to increment them all at the top of the block.

In our implementation, we attempt to minimize the number of counters executed at runtime. After generating basic blocks and attaching the source objects to their blocks, we analyze the blocks to determine which counters can be calculated in terms of other counters. If possible, a counter is computed as the sum of a list of counters (+counters) minus the sum of a list of counters (-counters). This complicated the internal representation of counters and the generation of counters, but decreases the overhead of profiling. [14]

To instrument block-level profiling, we reuse the above infrastructure by creating fake source objects. When a file is compiled, we reset global initial block number to 0, and create a fake source file descriptor based on the file name. When creating blocks, each block is given a source object using the fake file descriptor, and using the blocks number as the starting and ending file position. This fake source object is used when block-level profiling is enable. This fake source is ignored and the list of sources from the source code is used when source-level profiling is enable. [15]

4.3 Storing and Loading profile data

We store profile data by creating a hash table from source file names to hash tables. Each second level hash table maps the starting file position of the expression to the weighted count of the expression. This lookup table is only populated after loading profile data from a file and not from a current profiled run. After loading profile data, it is accessible through `profile-query-weight`.

Profile data is not immediately loaded into the lookup table after a profiled run of a program. Profile data must first be dumped via `profile-dump-data` and then loaded via `profile-load-data`.

To dump profile data, the run time gathers up all profile counters. Recall that some counters are computed indirectly in terms of other counters. The values for these indirect counters are computed.

[12] TODO: Make mention of how this affects pattern-matching optimizations, i.e. a compiler that uses nanopass.

[13] TODO: Mention how profile info can be used for coverage checking?

[14] TODO: This explanation is probably wrong

[15] TODO: Maybe an example of creating fake sources

These values with their associated source objects are then written to a file. [16]

To support loading multiple data sets, we do not load execution counts directly into the lookup table. Instead we compute the percent of max for each counter. Before loading a new data set, we find the maximum counter value. Each weighted count is computed as a percent of the maximum counter value. If an entry for a source already exists in the lookup table then we compute the weighted average of the previous entry and the counter we're currently loading. We store the weighted count and the current weight in the lookup table, incrementing the weight by one with each new data set.

5. Related and Future Work

[17] [18] Modern systems such as GCC, .NET, and LLVM use profile directed optimizations [11, 12, 15]. However, these systems provide mostly low level optimizations, such as optimizations for block order and register allocation. In addition to limiting the kinds of optimizations the compiler can do, this low-level profile information is fragile.

Recently there has been work to give programmers advice on which data structure to use http://dx.doi.org/10.1109/CGO.2009.36, but with our techniques we can automagically optimize the generated code instead of just advice the programmer.

GCC profiles an internal control-flow graph (CFG). To maintain a consistent CFGs across instrumented and optimization builds, GCC requires similar optimization decisions across builds. By associating profile information with source expression we can more easily reuse profile information [3]. In our system, all profile information for a source file is usuable as long as the source file does not change.

.NET provides some higher level optimizations, such as function inlining and conditional branch optimization similar to `exclusive-cond` and `case` presented here. To optimize `switch` statements, .NET uses *value* profiling in addition to execution count profiling [15]. By probing the values used in a switch statement, the compiler can attempt to reorder the cases of the `switch` statement. [19]

The standard model for profile directed optimizations requires the instrument-profile-optimize workflow. LLVM has a different model for profile directed optimization. LLVM uses a runtime reoptimizer that monitors the running program. The runtime reoptimizer can profile the program as it runs "in the field" and perform simple optimizations to the machine code, or call off to an offline optimizer for more complex optimiztions on the LLVM bytecode.

Meta-programs generate code at compile time, so the examples presented in section 3 require the standard instrument-profile-optimize workflow. However, because we expose an API to access profiling information, we could use this system to perform runtime decisions based on profile information. To truly be beneficial, this requires keeping the runtime overhead of profiling very low, which is not usually the case [3, 4]. However, our techniques for reducing the number of counters and our careful representation of profile forms allows accurate source profiling with little overhead [20].

[16] TODO: I'm not 100% sure about how this works and I need to be. Some of the racket peoples were asking.

[17] TODO: felleisen04,tobin-hochstadt06

[18] TODO: I'm not sure what I'm doing with this section yet.

[19] TODO: Value probes seem like a pretty ad-hoc method to get a very specific optimization. I don't know if I want to say that.

[20] TODO: measure overhead on a standard set of benchmarks. The benchmarks I ran at cisco suggest ∼10% overhead, but those are not publically accessible. This sentence belongs in implementation

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