New lms frontend and staged computation graphs

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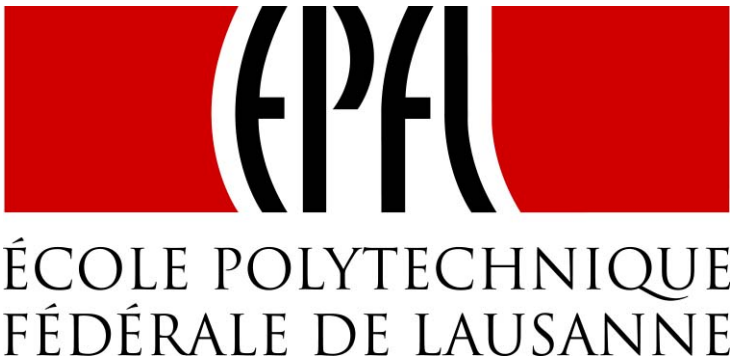

Abstract

In this report, we explore staging, in particular the LMS framework and the development of its new frontend whose aim is ease the writing of staged dsl through, among others, shadowing of types. We also explore the usage of this new frontend for a particular case study: Staged computation graphs.

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Introduction

If programming can be considered as an art, then programming languages are the brush of the artists. The tools are chosen according to individual preferences, and of course the constraints of the desired final work. One of those major constraints is efficiency. Efficiency is less crucial nowadays than it was back when computing power was expensive and scarce, but it is still a very desirable goal. Efficiency can be achieved by writing explicitely and very precisely each step of the program. To enable this, some programming languages are relatively close from the model of the hardware. Those programming languages are called "low-level", because close from the machine and thus distant from the heights of abstraction. But as programs grow more complex, the need for abstraction does too.

To raise abstraction power, expressive languages with complex compilers were made. Ironically, the first programmng language, lambda-calculus, was the epitomy of abstraction and thought of before the first very computer to execute it. Those languages, mostly from the functionnal programming world, aim the user to express the intent than the steps, the what rather than the how. The compilers needed for them are heavy machinery that applies all sort of optimization before translating source code to machine language. The more abstract the language, the more gap there is to fill, and the more compilers have opportunity to optimize.

Hence, in an ideal world, we can achieve **abstraction without regret**, writing very abstract programs compiled with optimal efficiency for any platform and any hardware. Unfortunately, we are not there yet and expert implementors are still in need. So should we just throw all our efforts into writing the ultimate compiler for the ultimate language ?

Growing complexity in compiler is not the panacea. In a wide range of programs, compilers are limited by the lack of domain specific knowledge. Indeed, constraining a program to one specific domain open the door for a wide range of specific optimizations. Furthermore, code generation by "macro" is a rather poor way to enable the further abstraction brought by code generation.

One solution to both issue could be to extend the compiler for each domain and having a very powerful macro system. The other one is to write specific domain-specific language in a staged environment. To avoid reinventing the wheel, embedded DSL is a nice compromise between specialized and general-purpose languages. It is this embedded DSL staged meta-programming path that is explored with LMS, a scala library for runtime code generation. In this report, we will explore a new lms implementation that offer a new user frontend, more convenient for the end-user and with multiple benefits enabled by extended typeclass usage. We also cover a case study of lms applied to the domain of computation graphs.

1. LMS

Why staging

To see the benefits of a staged-metaprogramming, we will start by an example where it benefits shine: sparse vector multiplication.

```
val v1: IndexedSeq
val block = {
    val prng = new util.Random(123)
    def rd(i: Int) = prng.nextInt(i)

    def newVec(size: Int) = {
        val a = Array.fill(size)(0)
        for (i <- (1 to 10))
            a(rd(size)) = rd(100)
        a
    }

    val v2 = newVec(1000)
```

```
    v1.zip(v2) map { case (x1, x2) => x1 * x2 } sum
}
```

This work but it is terribly inefficient. What about all those 0 multiplications. Surely, we can do something better. There is 3 cases.

- v1 and v2 are both known at compile time
- v1 is known at compile time
- v1 and v2 are both only known at runtime

In all three cases, staged-metaprogramming is able to generate efficient code that avoid the (1000 [zip]+ 1000 [*]) operations at runtime and reduce it to 10 operations (no more zip) and even 0 operations in the first case!

How ? Well it is all about available information. We will start with the first case which is the simplest to understand: We know at staging time all the data and all the operation that is applied to the data. Instead of waiting for runtime to apply those operations, we can generate a new block that is strictly equivalent. *Note* that to ensure equivalence, we use a fixed seed so that the number generation is deterministic and the current state of the world at execution is not relevant. So the generated code can be reduced to:

```
val stagedBlock = C
```

where C is a constant which value depend on v1

In the second and third case the code can be generated to this reduced form:

//TODO

```
val stagedBlock = {
    val x0 = new util.Random(123)
    val x1 = v1(x0.nextInt(100)) * rd(100)
    val x2 = v1(rd(100)) * rd(100)
    val x3 = x2 + x1
    val x4 = v1(rd(100)) * rd(100)
}
```

LMS

Lightweight Modular Staging (LMS) is a library written in Scala that enable staged meta-programming. Meta-Programming is the art of writing computer programs that can handle other programs as data. Thus, they are able to reason about programs, which they are themselves, hence the name. In staged meta-programming, the goal is to generate new programs from annotated programs. Those annotations are called staged annotions. The program source is called the **meta-program**. The program being generated is the the **object program**. The generation can go through multiple stage. Each stage is another transformation that can leverage new informations to build the final program. LMS is heterogenous: the meta-program and the object program can be written in different programming languages (eg: generating C).

In LMS, the meta-program is written in a subset of Scala. This subset is:

- every operations on any type that has a "lifted" implementation. Int/Float/Double/Array and more are already part of LMS (*batteries included*)
- if-then-else
- for-loop/while
- lambda-functions and named functions
- equalities

We will see later what a lifted implementation is but for now let say that any type can be added to LMS as long as we write some appropriate implementation for it. Other projects like scala-native are focused only on LLVM generation but supports the full scala-language.

Staging

In meta-programming, the staged annotations can usually take multiple forms:

- String (Yes, you read that right, the full program is written as a string)
- Abstract-Data-Type (Add(Int(2), Int(3)))
- quasiquotes (Meta-OCaml)

The LMS way is ... neither. It is based on a virtualized extension of Scala, DSL whose operations on lifted types creates an expression tree

and deep reuse of the embedding language order. Those combined achieve a transparent and convenient meta-programming environment for the user because it is virtually no different from a non staged program. We will analyze those three components of LMS below.

Lifted types

A lifted type represents that same type at a future stage. For instance, the lifted type of an integer is a declaration that once staged, this same value will represent an integer. So instead of manipulating an integer directly, you manipulate an "integer once staged".

Although similar those programs are different:

This one is a standard program stating that a, b are integers and that c is their sum.

```
val a: Integer
val b: Integer
cal c: Integer = a + b
```

This one is a meta-program stating that a, b will be integers in the object program and that c in your object program should represent their sum.

```
val a: LiftedInteger
val b: LiftedInteger
```

```
val c: LiftedInger a + b
```

Notice that even though we use the same operator +, we necessary have to redefine it for LiftedInteger. But instead of actually summing integers, this new + operator will build the right Internal Represenation for this object-program operation.

Internal representation and the Exp tree

In order to manipulate meta-programs, it has to first convert the source code of a meta-program into a more convenient representation, easier to manipulate. This representation is called Internal Representation (IR). The IR of LMS is based on typed expression trees and single static assignments (SSA). This representation is a «sea of nodes» representation.

```
trait Exp[+T]
// Constant expression of type T
case class Const[T](x: T) extends Exp[T]
// Symbol referencing a definition of type T
case class Sym[T](id: Int) extends Exp[T]
// Composite node that is defined by a library or DSL author
trait Def[+T]
// Statement in the IR
case class TP[+T](sym: Sym[T], rhs: Def[T])
```

An assignment links a symbol to a definition. A definition is a composite node that represents an operation on other expressions (eg: Minus(e1:Exp[Int], e2:Exp[Int]) extends Def[Int])) and defines the result type.

The expression tree in itself is a typed tree made of only two leaves: Constants and Symbols: «Wait, where are the nodes ?». The nodes are in fact the symbols, or more precisely, the composite node Def that the symbol represents (As stated by a TP). Constants are meta-programs values (eg: a meta-program "val a:LiftedInteger = 2" is represented in the IR as this constant expression: Const(2).

By using Scala pattern extractors and implicit conversions, we can reconstruct and manipulate this tree as if it was made only of Def and Const which is more natural.

For instance:

```
val a: Integer = ...
val b: Integer = ...
cal c: Integer = (a + b) - (a * b)
```

is represented as:

```
TP(Sym(0), ...)
TP(Sym(1), ...)
TP(Sym(2), Add(Sym(0), Sym(1)))
TP(Sym(3), Times(Sym(0), Sym(1)))
TP(Sym(4), Minus(Sym(2), Sym(3)))
```

But can be manipulated as:

```
Minus(Add(d, e), Times(f, g))
```

We will not describe further the IR since this project focus on the frontend. It will be clearer later what separates the backend from the frontend. But a simple informal definition is that the subset of scala that is available to the user to write meta-programs are the frontend. This include the lifted types interface and the building of the IR as a tree mode solely of the Def hybrid nodes. The IR representation as a sea of nodes, the IR manipulation such as transformers and traversals and code generation are the backend.

Lifted types and DSL operations

The previous frontend of LMS was representing lifted types as wrapped in a Rep monad. `LiftedInteger` would be written as`Rep[Int]`. The idea is that if A is the expected type in the object-program then we manpulate its Rep-resentation. This monad was the staging annotation.

The way to define operations on DSL was to define operators in scope that would manipulate the given Rep.

For instance, the DSL provided operations on Integers such as

```
def infix_+(e1: Rep[Int], e2:Rep[Int])
```

So as long as the corresponding methods or operators were in scope, the user was able to manipulate conveniently `Rep[A]` as if they were `A`.

Scala virtualization

In order to enable the if-then-else/loops and other control, we use a modified version of the Scala language: scala-virtualized. Scala-virtualized enable to overload the controls as common functions: eg: 'if (t1) t1 else t2 becomes' '__ifThenElse(t1, t2, t3)'. We can use this overloading to extend the controls to lifted type.

Smart constructors

deep reuse of the embedding language order

library author

delite

user

2. The new frontend

Lift

Typeclass

Typeclass overloading

Primitives types and collections

3. Computation Graph

Computation graphs are directed graph made of nodes that represent a computation. It is an abstract model that can generalize many functions. It is very common in distributed computing and it is how most deep learning (TensorFlow, Deeplearning4j) represents their neural networks models.

Each node has 0 or more inputs and 0 or n outputs and 1 operation. Having 0 inputs is the special case of Input nodes and having 0 output is the special case of output nodes. The input nodes form the input layer. The output nodes form the output layer. We will only consider feedforward computation graphs without any cycles.

An example of a node can be the Add node. It takes two entry and output their sum.

The benefits of staging for Computation Graph is that there it would be advantageous to separate the construction of the graph and the execution of computation on this graph. Indeed, it is possible to check some properties on the computation graph that ensure that the graph has proper form. Furthermore, it is possible to apply transformation to the graph such as

computing the gradient of the function represented by the graph. Last but not least, computation graph are abstractions that are convenient to build, conceptualize and handle but not very efficient because of the level of abstraction. Fortunately, after staging unecessary indirections are removed and the whole function is linearized into the bare required operations.

One of the clear benefits of using types as staged annotations is the ability to share codes between non staged programs and meta-programs. Indeed, the graph can set the type of data it manipulates as an abstract type member. Then depending on the type of graph and the type of nodes the graph may contain, this type can be upper bounded by the appropriate interface.

```
trait Graphs {

  type Data
  type Input = List[Data]
  type Output = Data
  type G <: Graph
  type N <: Node
  type R = (N, List[String])
  trait Node { ... }

  ...

  trait Graph {

    //check if there is cycle in the graph
    checkCycle()
    def inputSize: Int
    def nodes: Map[String, R]
    def apply(input: List[Data]) = { ... }
    def checkCycle() = { ...  }
    def forward(input: List[Data]): (Data, Map[String, Data]) = { ... }
```

```
}


trait DerivableGraphs extends Graphs {

  def zero: Data
  def one: Data

  type Data <: AddTimeAble[Data]
  type Derivatives = List[Data]
  type N = DerivableNode
  type G = DerivableGraph
  ...
}
```

`AddTimeAble[Data]` guarantees that Data has the operations `+` and `*` necessary for derivations.

Here Data can either be either `dsl.Int` for a staged computation graph or else a simple `scala.Int` (or at least a wrapper that implements AddTimeAble)

Cycle check

A staged computation graph builds the graph during staging. This means that all the verification that should happen during the building of the graph can happen during staging. This adds additional guarantees at runtime, here that our staged computation graph doesn't contain any cycle.

Arithmetic

Benchmark

DerivableGraph

Backpropagation

MatrixGraph

Dimensions check

Conclusion

blablabla

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