A Compiler-Compiler for DSL Embedding

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Abstract
In this paper, we present a framework to generate compilers for embedded domain-specific languages (EDSLs). This framework provides facilities to automatically generate the boilerplate code required for building DSL compilers on top of extensible optimizing compilers. We evaluate the practicality of our framework by demonstrating several use-cases successfully built with it.

CCS Concepts • Software and its engineering → Software performance; Compilers;

Keywords Domain-Specific Languages, Compiler-Compiler, Language Embedding

1 Introduction
Everything that happens once can never happen again. But everything that happens twice will surely happen a third time.

– Paulo Coelho, The Alchemist

Domain-specific languages (DSLs) have gained enormous success in providing productivity and performance simultaneously. The former is achieved through their concise syntax, while the latter is achieved by using specialization and compilation techniques. These two significantly improve DSL users’ programming experience.

Building DSL compilers is a time-consuming and tedious task requiring much boilerplate code related to non-creative aspects of building a compiler, such as the definition of intermediate representation (IR) nodes and repetitive transformations [2]. There are many extensible optimizing compilers to help DSL developers by providing the required infrastructure for building compiler-based DSLs. However, the existing optimizing compilation frameworks suffer from a steep learning curve, which hinders their adoption by DSL developers who lack compiler expertise. In addition, if the API of the underlying extensible optimizing compiler changes, the DSL developer would need to globally refactor the code base of the DSL compiler.

The key contribution of this paper is to use a generative approach to help DSL developers with the process of building a DSL compiler. Instead of asking the DSL developer to provide the boilerplate code snippets required for building a DSL compiler, we present a framework which automatically generates them.

More specifically, we present Alchemy, a language workbench [9,12] for generating compilers for embedded DSLs (EDSLs) [14] in the Scala programming language. DSL developers define a DSL as a normal library in Scala. This plain Scala implementation can be used for debugging purposes without worrying about the performance aspects (handled separately by the DSL compiler).

Alchemy provides a customizable set of annotations for encoding the domain knowledge in the optimizing compilation frameworks. A DSL developer annotates the DSL library, from which Alchemy generates a DSL compiler that is built on top of an extensible optimizing compiler. As opposed to the existing compiler-compilers and language workbenches, Alchemy does not need a new meta-language for defining a DSL; instead, Alchemy uses the reflection capabilities of Scala to treat the plain Scala code of the DSL library as the language specification.

A compiler expert can customize the behavior of the predefined set of annotations based on the features provided by a particular optimizing compiler. Furthermore, the compiler expert can extend the set of annotations with additional ones for encoding various domain knowledge in an optimizing compiler.

This paper is organized as follows. In Section 2 we review the background material and related work. Then, in Section 3 we give a high-level overview of the Alchemy framework. In Section 4 we present the process of generating a DSL compiler in more detail. Section 5 presents several use cases built with the Alchemy framework. Finally, Section 6 concludes.

2 Background & Related Work

In this section, we present the background and related work to better understand the design decisions behind Alchemy.

2.1 Compiler-Compiler

A compiler-compiler (or a meta compiler) is a program that generates a compiler from the specification of a programming language. This specification is usually expressed in a declarative language, called a meta-language.

Yacc [17] is a compiler-compiler for generating parsers specified using a declarative language. There are numerous systems for defining new languages, referred to as language workbenches [9,12], such as Stratego/Spoofax [19], Sugar* [8], KHEPERA [10], and MPS [16].

2.2 Domain-Specific Languages

DSLs are programming languages tailored for a specific domain. There are many successful examples of systems using
DSLs in various domains such as SQL in database management, Spiral [28] for generating digital signal processing kernels, and Halide [29] for image processing. The software development process can also be improved by using DSLs, referred to as language-oriented programming [40]. Cadelion [23] is a language workbench developed for language-oriented programming.

There are two kinds of DSLs: 1) external DSLs which have a stand-alone compiler, and 2) embedded DSLs [14] (EDSLs) which are embedded in another generic-purpose programming language, called a host language.

Various EDSLs have been successfully implemented in different host languages, such as Haskell [1, 14, 24] or Scala [21, 25, 30, 33]. The main advantage of EDSLs is reusing the existing infrastructure of the host language, such as the parser, the type checker, and the IDEs among others.

There are two ways to define an EDSL. The first approach is by defining it as a plain library in the host language, referred to as shallowly embedding it in the host language. A shallow EDSL is reusing both the frontend and backend components of the host language compiler. However, the opportunities for domain-specific optimizations are left unexploited. In other words, the library-based implementation of the EDSL in the host language is served an interpreter.

The second approach is deeply embedding the DSL in the host language. A deep EDSL is only using the frontend of the host language, and requires the DSL developer to implement a backend for the EDSL. This way, the DSL developer can leverage domain-specific opportunities for optimizations and can leverage different target backends through code generation.

2.3 Extensible Optimizing Compilers

There are many extensible optimizing compilers which provide facilities for defining optimizations and code generation for new languages. Such frameworks can significantly simplify the development of the backend component of the compiler for a new programming language.

Stratego/Spoofox [19] uses strategy-based term-rewrite systems for defining domain-specific optimizations for DSLs. Stratego uses an approach similar to quasi-quotation [39] to hide the expression terms from the user. For the same purpose, Alchemy uses annotations for specifying a subset of optimizations specified by the compiler expert. One can use quasi-quotes [26, 34] for implementing domain-specific optimizations in concrete syntax (rather than abstract syntax) similar to Stratego.

2.4 What is Alchemy?

Alchemy is a compiler-compiler, designed for EDSLs that use Scala as their host language. Alchemy uses the Scala language itself as its meta-language; it takes an annotated library as the implementation of a shallow EDSL and produces the required boilerplate code for defining a backend for this EDSL using a particular extensible optimizing compiler. In other words, Alchemy converts an interpreter for a language (a shallow EDSL) to a compiler (a deep EDSL).

Truffle [15] provides a DSL for defining self-optimizing AST interpreters, using the Graal [41] optimizing compiler as the backend. This system mainly focuses on providing just-in-time compilation for dynamically typed languages such as JavaScript and R, by annotating AST nodes. In contrast, Alchemy uses annotation on the library itself and generates the AST nodes based on strategy defined by the compiler expert.

Forge [38] is an embedded DSL in Scala for specifying other DSLs. Forge is used by the Delite [21] and LMS [30, 31] compilation frameworks. This approach requires DSL developers to learn a new specification language before implementing DSLs. In contrast, Alchemy developers write a DSL specification using plain Scala code. Then, domain-specific knowledge is encoded using simple Alchemy annotations.

Yin-Yang [18] uses Scala macros for automatically converting shallow EDSLs to the corresponding deep EDSLs. Thus, it completely removes the need for providing the definition of a deep DSL library from the DSL developer. However, contrary to our work, the compiler-translation of Yin-Yang is specific to the LMS [30] compilation framework. Also, Yin-Yang does not generate any code related to optimizations of the DSL library. We have identified the task of automatically generating the optimizations to be not only a crucial requirement for DSL developers but also one that is significantly more complicated than the one handled by Yin-Yang.

3 Overview

Figure 1 shows the overall design of the Alchemy framework. Alchemy is implemented as a compiler plugin for the Scala programming language. After parsing and type checking the library-based implementation of an EDSL, Alchemy uses the type-checked Scala AST to generate an appropriate DSL compiler. The generated DSL compiler follows the API provided by an extensible optimizing compiler to implement transformations and code generation needed for that DSL.

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1We decided to implement Alchemy as a compiler plugin rather than using the macro system of Scala, due to the restrictions imposed by def macros and macro annotations.
There are two different types of users for Alchemy. The first type is a DSL developer, who is the end-user of the Alchemy framework for defining a new DSL together with a set of domain-specific optimizations specified by a set of annotations. A DSL developer is a domain expert, without too much expertise in compilers.

The second type of users is a compiler expert, who is not necessarily knowledgeable in various domains; instead, she is an expert in building optimizing compilers. In particular, a compiler expert has detailed knowledge about the internals of a specific extensible optimizing compiler. Thus, she can use the API provided by the Alchemy framework to specify how the definition of an annotated Scala library is converted into the boilerplate code required for a DSL compiler built on top of an extensible optimizing compiler. Furthermore, she can extend the set of existing annotations provided by Alchemy, for encoding the domain knowledge to be used by an optimizing compiler.

4 Compiler-Compilation

In this section, we give more details on the process of generating a DSL compiler. First, we present the annotations defined by the Alchemy framework. Then, we show the process of gathering the DSL information from an annotated library. Afterwards, through an example we give more details on the process of generating a DSL compiler based on the gathered DSL information. Then, we show how Alchemy uses the implementation body of the annotated library for building DSL compilers. Finally, we show the process of generating EDSL compilers using a well-known embedding technique through our running example.

4.1 Alchemy Annotations

Deep Types. The DSL developers use the @deep annotation for specifying the types for which they are interested in generating a corresponding deep embedding. In other words, this annotation should be used for the types that are actually participating in the definition of a DSL, rather than helper classes which are used for debugging, profiling, and logging purposes.

Reflected Types. The @reflect annotation is used for annotating the classes the source code of which the DSL developers have no access to. This annotation is used in Alchemy for a) annotating the methods of the Scala core libraries, such as HashMap, ArrayBuffer, etc. which are frequently used, as well as for b) providing alternative implementations for the DSL library and the Scala core library.

User-Defined Annotations. Alchemy allows compiler experts to define their custom annotations, together with the behavior of the target DSL compiler for the annotated method.

4.2 Gathering DSL Information

The Alchemy framework inspects the Scala AST of the given annotated library after the type checking phase of the Scala compiler. Based on the typed Scala AST, Alchemy produces the information about the shallow version of the EDSL by building ShallowMethod, ShallowType, and ShallowDSL objects, corresponding to the DSL methods, DSL types, and the whole DSL, respectively.

A ShallowMethod instance has the symbol of the DSL method (the sym parameter) and the AST of its body, if available. Also, this instance returns the list of annotations that the DSL developer has used for the method (annotations) and its parameters (paramAnnots).

A ShallowType instance contains the information of the DSL type (the tpe parameter) and the list of its methods. In addition, this instance has the list of annotations used for the type (annotations) and the type it reflects (reflectType) in the case where it is annotated with @reflect.

Finally, a ShallowDSL instance has the information of all DSL types that are annotated with @deep. Next, we show how this information is used to build a compiler for a simple DSL.

4.3 Generating an EDSL Compiler

Let us consider a DSL for working with complex numbers as our running example. For this DSL, we generate a DSL compiler using a simple form of expression terms as the intermediate representation, which is used by compilation frameworks such as Kiama [37].

Figure 2. The API of Alchemy for compiler experts.
4.4 Lifting the Implementation

As Figure 2 shows, Alchemy also provides two methods for lifting the expression and the type of the implementation.

4.5 Generating a Polymorphic EDSL Compiler

Let us consider the third version of the Complex DSL, shown in Figure 7. This version has an additional construct for negating a complex number, specified by the unary-_ method.
Subtracting two complex numbers is a syntactic sugar (annotated with @sugar) for adding the first complex number with the negation of the second complex number.

Polymorphic embedding [13] (or tagless final [3]), is an approach for implementing EDSLs where every DSL construct is converted into a function (rather than an ADT) and the interpretation of these functions are left abstract. Thus, it is possible to provide such abstract interpretations with different instances, such as actual evaluation, compilation, and partial evaluation [3, 13].

Figure 8 shows the polymorphic embedding interface generated by Alchemy for the third version of the Complex DSL. The type member Rep[T] is an abstract type representation for different interpretations of Complex DSL programs.

Figure 9 shows the generated deep embedding interface for the polymorphic embedding of the Complex DSL. Instead of using ADTs for defining IR nodes, this time we use generalized algebraic data types (GADTs). The invocation of each DSL construct method results in the creation of the corresponding node. As the subtraction of two complex numbers is a syntactic sugar, no corresponding IR node is created for it. Instead, the complexSub method results in the invocation of the complexAdd and complexNeg methods, which is generated using the liftExp method of Alchemy.

Figure 10 shows the lifted expression of the example of Figure 6. In this case, instead of converting expressions to their ADT definition, Alchemy converts them to their corresponding DSL method definition in polymorphic embedding. In addition, this figure shows the generated IR nodes for this program, in which the subtraction construct is desugared into the addition and negation nodes. Note that the negation of zero and addition with zero can be further simplified by providing yet another optimized interface implementation in polymorphic embedding. Examples of such simplifications are given later in Section 5.4.

Up to now, we have used simple expression terms for the definition of IR nodes. Alchemy can easily generate other types of IR nodes such as A-Normal Form [11], where the children of a node are either constant values or variable accesses. This means that all non-trivial sub-expressions are let-bound, which helps in applying optimizations such as common-subexpression elimination (CSE) and dead-code elimination (CSE). Such normalized types of IR nodes are used in various optimizing compilers such as Graal [41], LMS [30], Squid [26], and SC. We will see more detailed examples of SC in the next section.
// lifted expression in polymorphic embedding
complexSub(
    complexNew(
        doubleConst(2), doubleConst(3)
    ), complexZero()
)
// generated IR nodes
ComplexAdd(
    ComplexNew(
        DoubleConstant(2), DoubleConstant(3)
    ), ComplexNeg(
        ComplexZero()
    )
)

Figure 10. Polymorphic embedding version of the example in Figure 6, and the generated IR nodes.

Figure 11. Overall design of SC used with Alchemy.

5 Use Cases and Evaluation

In this section, we present the use cases built on top of Alchemy. We provide an extended set of annotations and show their usage. Finally, we evaluate the productivity of the DSL developer.

5.1 SC

SC (the Systems Compiler) is a compilation framework for building compilation-based systems in the Scala programming language. Different system component libraries can be considered as different DSLs, for which system developers extend SC to build DSL compilers. To hide the internal implementation details of the compiler, Alchemy provides an abstraction layer between the system component libraries and the SC optimizing compiler itself. Figure 11 shows the overall design of Alchemy and SC, which operates as follows.

The system developer (who is actually a DSL developer) uses the SC plugin of Alchemy to create a DSL compiler. Many systems optimizations are automatically converted by Alchemy to functions that manipulate the IR of the compiler. The system developer uses a set of annotations provided by the compiler expert of the SC framework, to specify the IR transformations. To provide more advanced domain-specific optimizations that cannot be encoded by annotations, as well as compilation phases, the system developer uses the transformation API provided by SC.

SC converts the systems code to a graph-like intermediate representation (IR). As SC follows the polymorphic embedding approach [13] for deeply embedding DSLs, SC uses Yin-Yang [18] which applies several transformations (e.g., language virtualization [4]) in order to convert the plain Scala code into the corresponding IR.

We have used SC to build two different compilation-based query engines: a) an analytical query processing engine [35, 36], and b) a transactional query processing engine [6].

From the perspective of the abstraction level of a program, the transformations are classified into two categories. First, optimizing transformations transform a program into another program on the same level of abstraction. Second, lowering transformations convert a program into one on a lower abstraction level. SC provides a set of built-in transformations out-of-the-box. These mainly consist of generic compiler optimizations such as common-subexpression elimination (CSE), dead-code elimination (DCE), partial evaluation (PE), etc.

The last phase in the SC compiler is code generation where the compiler generates the code based on the desired target language. Observe that since each lowering transformation brings the program closer to the final target code, this provides the excellent property that code generation (e.g., C code generation) in the end basically becomes a trivial and naive stringification of the lowest level representation.

For converting from host to target languages, SC can make use of the same infrastructure. To do this conversion, a DSL developer only has to express the constructs and the necessary data-structure API of the target language as a library inside the host language. Then, there is no need for the DSL developer to manually provide code generation for the target language using internal compilers APIs as is the case with most existing solutions. In contrast, Alchemy automatically generates the transformation phases needed to convert from host language IR nodes to target language IR nodes (e.g., from Scala to C).

An important side-effect of our design is that since the plain Scala code of a system does not require any specific syntax, type or IR-related information from SC, this code is directly executable using the normal Scala compiler. In this case, the Scala compiler will ignore all Alchemy annotations, and interpret the code of the system using plain Scala. Alchemy can thus be seen as a system for converting a system interpreter (which executes the systems code unoptimized) into the corresponding system compiler along with its optimizations.

Next, we briefly provide more details about the two categories of transformations that SC supports.

\(^2\) We note that Yin-Yang, in contrast to our work, handles only the conversion from plain Scala code to IR, without providing any functionality related to code optimization of the systems library.
5.2 SC Transformations

SC classifies the transformations into two categories, which we present in more detail next while also highlighting differences from previous work in each class.

Online transformations are applied while the IR nodes are generated. Every construct of a DSL is mapped to a method invocation, which in turn results in the generation of an IR node [3, 13]. By overriding the behavior of that method, an online transformation can result in the generation of a different (set of) IR node(s) than the original IR node. Even though a large set of optimizations (such as constant folding, common subexpression elimination, and others) can be expressed using online transformations, some optimizations need to be preceded by analysis over the whole program.

For a restricted set of control-flow constructs, namely structured loops, it is possible to use the Speculative Rewriting [22] approach in order to combine the data-flow analysis with an online transformation, thus bypassing the need for a separate analysis pass. However, we have observed that there exists an important class of transformations in which the corresponding analysis cannot be combined with the transformation phase. This class of optimizations, which cannot be handled by existing extensible optimizing compilers, is presented next.

Offline transformations need whole program analysis before applying any transformation. Figure 12 shows the SC offline transformation API. The analysis construct specifies the information that should be collected during the analysis phase of a transformation. The rewrite construct specifies the transformation rules based on the information gathered during the analysis phase. Finally, the remove construct removes the pattern specified in its body.

The Alchemy annotation processor takes care of converting the Scala annotations of the systems library, which express optimizations, into IR transformers which manipulate the intermediate representation of SC. This is explained in more detail in Section 5.4.

5.3 SC Annotations

In this section, we present in more detail the different categories of annotations implemented for SC.

Side-Effects. These are annotations that guide the effect system of the optimizing compiler. For example, a method annotated with @pure denotes that this method does not cause any side effects and the expressions that call this method can be moved freely throughout the program. In addition, Alchemy provides more fine-grained effect annotations that keep track of read and write mutations of objects. More precisely, if a method is annotated with read or write annotations, then there exists a mutation effect over the specific object (i.e., this) of that particular class. Similarly, an annotated argument may include read or write effects over that argument.
**Inline.** The @inline annotation guides the inlining decisions of the compiler. This annotation can be applied to methods, whole classes as well as class fields, with different semantics in each case. Methods annotated with the @inline annotation specify that every invocation of that method should be inlined by the compiler. For classes, the @inline annotation removes the abstraction of the specific class during compilation time. In essence, this means that the methods of an inlined class are implicitly annotated with the inline annotation and are subsequently inlined. This makes inlined classes in Alchemy semantically similar to value classes [32]. Finally, a mutable field of a class can also be annotated with @inline, which means that all the usages of this field are partially evaluated during compilation time.

Figure 13 shows the scan and hash-join operators annotated with the @inline annotation. In this example, all methods of the HashJoinOp class are automatically inlined, as the HashJoinOp class is marked with the @inline annotation. Furthermore, the mutable field mode is partially evaluated at compilation time and, as a result, the corresponding branch in the consume method is also partially evaluated at compilation time. More concretely, both leftParent.init and rightParent.init invoke the consume method of the HashJoinOp class. However, the former inlines the code in the phase1 block whereas the latter inlines the phase2 code block. This is possible as mode is evaluated during compilation time and, thus, there is no need to generate any code for it and the corresponding if condition checks. We have found that there are multiple examples where such if conditions can be safely removed in our analytical query engine (e.g., in the case of configuration variables whose values are known in advance at startup time).

**Algebraic Structure.** These are annotations for specifying the common algebraic rules that occur frequently for different use cases. For example, @monoid specifies a binary operation of a type that has a monoid structure. In the case of natural numbers, @monoid specifies over the + operator represents that a+0=0+a=a. The annotation processor generates several constant folding optimizations which benefit from such algebraic structure and significantly improve the performance of systems that use them.

Furthermore, the @commutative annotation specifies that the order of the operands of a binary operation can be changed without affecting the result. This property is useful for applying constant folding on cases in which static arguments and dynamic arguments are mixed in an arbitrary order, thus hindering the constant folding process. For example, in the expression 1 + a + 2, constant folding cannot be performed without specifying that the commutativity property of addition on natural numbers is applicable in this case. However, if we push the static terms to the left side of the expression while we generate the nodes, we generate the IR which represents the expression 1 + 2 + a instead of the previous expression. Then, it becomes possible to apply constant folding and get the expression 3 + a.

### 5.4 Generating Transformation Passes

As discussed in Section 5.2, these transformation passes are classified into two categories: online and offline transformations. In this section, we demonstrate how Alchemy generates online and offline transformation passes.

**Generating Online Transformations.** In general, Alchemy uses node generation (online transformation) in order to implement the appropriate rewrite rules for most annotations. As we discussed in Section 4.5, every construct of a DSL is classified into two categories: online and offline transformations. In this section, we demonstrate how Alchemy generates online transformation passes.

For example, in the case of addition on natural numbers, the default behavior for the method int_plus is shown in lines 1-3 of Figure 15. This method generates the IntPlus IR node, which is also automatically generated by Alchemy. However, when this method is annotated with the @monoid and @commutative annotations, this results in the generation of an online transformation. More specifically, the annotated method automatically generates the code shown in lines 5-14 of the same figure. First, as the method is pure, SC checks if both arguments are statically known. This is achieved by checking if the expressions are of Constant type or not. In this case, SC performs partial evaluation by computing the result through the addition of the arguments. Second, if only one of the arguments is statically known and it is equal to 0, the monoid property of this operator returns the dynamic operand. Third, if only one of the arguments is statically known (but it is not zero), then the static argument is pushed as the left operand, as we know that this operator is commutative. Finally, if none of the previous cases is true, then the default behavior is used and the original IntPlus IR node is generated.

Alchemy also generates an online transformation out of the @inline annotation. For methods with this annotation, instead of generating the corresponding node, Alchemy generates the nodes for the body of that method. In the special case of dynamic dispatch, the concrete type of the object is looked up and based on its value Alchemy invokes the appropriate method.

For example, the annotated code for the scanning operator of the analytical query engine, shown in Figure 13, generates the compiler code shown in Figure 16. There the scanOpInit method represents the corresponding method which is invoked in order to generate an appropriate IR. As is the case with integer addition, the default behavior of this method, which results in creating the ScanOpInit IR node, is shown in lines 1-3. The rest of the code presents the implementation of the @inline annotation for this operator, which results in inlining the body of this method while generating
the IR node. The method `scanOpInit` is automatically generated by Alchemy which generates the body of the `init` method. As described earlier, all method invocations lead to the generation of the corresponding IR nodes. For example, `__whileDo` results in creating an IR node for a `while` loop.

Finally, for inlining the `init` method of the `Operator` class, we need to handle dynamic dispatch, as we described earlier. We do so by redirecting to the appropriate method based on the type of the caller object. An alternative design is to use multi-stage programming for encoding the fact that the objects of `Operator` class are staged away. This is achieved by generating the deep embedding interface of all operator classes as partially static. With a similar design, one can support staging for other libraries implemented using design patterns that require abstraction overheads such as generic programming [20, 42].

**Generating Offline Transformations.** The generated transformations are not limited to online transformations. Alchemy also generates offline transformation passes. Figure 17 shows the implementation of three different transformations for the `Seq` class\(^3\), in plain Scala code. The first implementation uses a linked list for storing the elements of the sequence. The second implementation stores the elements in an array data-structure.\(^4\) Finally, the third implementation uses a `g_list` data-structure, provided by GLib. The generated transformation from this class can be used for using data structures provided by GLib in the generated C code.

These implementations can be used for debugging the correctness of the transformers. For using them in the DSL compiler, Alchemy generates offline transformations based on the `Operator` class. The second implementation stores the elements in a data-structure, provided by GLib. The generated transformation from this class can be used for using data structures provided by GLib in the generated C code.

\(^3\) By a `Seq` data type, we mean a collection where the order of its elements does not matter.

\(^4\) This implementation assumes that the number of the elements in the collection does not exceed `MAX_BUCKETS`. In cases where this assumption does not hold, one has to make the corresponding field mutable, and add an additional check while inserting an element.
Alchemy for Seq can be facilitated by using quasi-quotations [26, 27, 34]. More

Third, as we aim to give systems developers the ability to provide specific infrastructure for an external DSL, as opposed to the approach of Stratego/Spoofox [19]. Second, developers can annotate the source code with appropriate annotations, without the need to port it into another DSL, as opposed to the approach taken in Forge [38]. In other words, developers use the signature of classes and methods as the meta-data needed for specifying the DSL constructs, whereas in a system like Forge the DSL developer must use Forge DSL constructs to specify the constructs of the DSL. Third, as we aim to give systems developers the ability to write their systems in plain Scala code, we designed Alchemy so that developers can place the annotations on the systems code itself, whereas an approach like Truffle [15] focuses on self-optimizing AST interpreters. Thus, the latter annotates the AST nodes of the language itself.

5.5 Productivity Evaluation

We use Alchemy to automatically generate the compiler interface for a subset of the standard Scala library and two database engines: 1) an analytical query engine [35, 36], and 2) a transactional query engine [6]. Table 1 compares the number of LoCs5 of the library classes with the generated compiler interfaces. We make the following observations.

First, for the Scala standard library classes, the LoCs of the reflected classes are mentioned in the table. These classes provide the method signatures of their original classes and are annotated with appropriate effect and algebraic structure annotations (Section 5.3). However, in most cases, developers do not need to provide the implementation of the methods of these classes. As a result, the compiler interfaces of the Scala

Figure 17. Different transformations for the Scala Seq class. The transformations are written using plain Scala code.

Figure 18. The generated offline transformations by Alchemy for Seq based on arrays.

on the SC API (cf. Figure 12). Figure 18 shows the generated offline transformation for the implementation of the Seq data-structure using an array. This transformation lowers the objects of a Seq data structure into records with two fields: 1) the underlying array, 2) the current size of the collection. The nodes corresponding to each method of this data structure are then rewritten to the IR nodes of the implementation body provided in the reflected type.

Many offline transformations require inspecting the generated IR nodes to check their applicability. In some of these cases, compiler experts can provide annotations to generate the required analysis passes. However, in many cases, the analysis requires more features than the ones provided by the existing annotations. Implementing such analysis passes can be facilitated by using quasi-quotations [26, 27, 34]. More
details about the implementation of quasi-quotations and their usages are beyond the scope of this paper.

The aforementioned design provides several advantages over previous work. First, the Alchemy annotation processor uses Scala annotations. This means that there is no need to provide specific infrastructure for an external DSL, as opposed to the approach of Stratego/Spoofox [19]. Second, developers can annotate the source code with appropriate annotations, without the need to port it into another DSL, as opposed to the approach taken in Forge [38]. In other words, developers use the signature of classes and methods as the meta-data needed for specifying the DSL constructs, whereas in a system like Forge the DSL developer must use Forge DSL constructs to specify the constructs of the DSL. Third, as we aim to give systems developers the ability to write their systems in plain Scala code, we designed Alchemy so that developers can place the annotations on the systems code itself, whereas an approach like Truffle [15] focuses on self-optimizing AST interpreters. Thus, the latter annotates the AST nodes of the language itself.

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5We used CLOC [5] to compare the number of LoCs.
standard library classes can be generated with only tens of LoCs. The exception is the reflected classes responsible for generating offline transformations (e.g., Seq Transformation and HashMap Transformation), where the developer provides the implementation to which every method should be transformed into.

Furthermore, observe that the Int class contains more LoCs than the many other standard library classes. This is because each operation of this class encodes different combinations of arguments in its methods with other numeric classes (e.g., Int with Double, Int with Float, and so on). Furthermore, the generated compiler interface of this class is also longer than expected. This is because the generated compiler code contains the constant-folding optimization (Section 5.3), which is encoded by Alchemy annotations. In addition, for the query operators of the analytical query engine, the generated compiler interface encodes all online partial evaluation processes annotated using the @inline annotation. This results in the partial evaluation of mutable fields, function inlining, and virtual dispatch removal.

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### Table 1. The comparison of LoCs of the (reflected) classes of the Scala standard library and a preliminary implementation of two query engines together with the corresponding automatically generated compilation interface.

| Type              | Library | Compiler |
|-------------------|---------|----------|
| **Analytical Query Engine** |         |          |
| Query Operators   | 541     | 3456     |
| Monadic Interface | 156     | 407      |
| File Manager      | 254     | 291      |
| Aux. Classes      | 100     | 749      |
| **Transactional Query Engine** |         |          |
| In-Memory Storage | 45      | 294      |
| Indexing Data-Structures | 69     | 394      |
| Aux. Classes      | 58      | 364      |
| **Scala Library** |         |          |
| Boolean           | 18      | 255      |
| Int               | 85      | 970      |
| Seq               | 39      | 334      |
| Seq Trans.        | 176     | 329      |
| Array             | 39      | 306      |
| ArrayBuffer       | 52      | 453      |
| HashMap           | 32      | 259      |
| HashMap Trans.    | 162     | 305      |
| C GLib            | 181     | 729      |
| Other Classes     | 936     | 7007     |
| **Total**         | 2943    | 16902    |
