Source Matching and Rewriting

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Abstract

A typical compiler flow relies on a uni-directional sequence of translation/optimization steps that lower the program abstract representation, making it hard to preserve higher-level program information across each transformation step. On the other hand, modern ISA extensions and hardware accelerators can benefit from the compiler’s ability to detect and raise program idioms to acceleration instructions or optimized library calls. Although recent works based on Multi-Level IR (MLIR) have been proposed for code raising, they rely on specialized languages, compiler recompilation, or in-depth dialect knowledge. This paper presents Source Matching and Rewriting (SMR), a user-oriented source-code-based approach for MLIR idiom matching and rewriting that does not require a compiler expert’s intervention. SMR uses a two-phase automaton-based DAG-matching algorithm inspired by early work on tree-pattern matching. First, the idiom Control-Dependency Graph (CDG) is matched against the program’s CDG to rule out code fragments that do not have a control-flow structure similar to the desired idiom. Second, candidate code fragments from the previous phase have their Data-Dependency Graphs (DDGs) constructed and matched against the idiom DDG. Experimental results show that SMR can effectively match idioms from Fortran (FIR) and C (CIL) programs while raising them as BLAS calls to improve performance.

1 Introduction

Idiom recognition is a well-known and studied problem in computer science, which aims to identify program fragments [4, 8, 20, 21, 30, 38]. Although idiom recognition has found a niche in compiling technology, in areas like code generation (e.g., instruction selection) [2, 3, 19, 37], its broad application is considerably constrained by how modern compilers work. A typical compiler flow makes a series of transformations that lowers the level of abstraction from source to machine code, with the goal of optimizing the code at each level. One such example is the Clang/LLVM compiler [28] which starts at a high-level language (e.g., C or Fortran) and gradually lowers the abstraction level to AST, LLVM IR, Machine IR, and finally binary code. After lowering from one level to another, program information is lost, thus restricting the possibility of simultaneously combining optimization passes from different abstraction levels.

Until recently, there was no demand for combining optimization passes from distinct abstraction levels, mainly due to two reasons. First, although many languages claim to implement higher-level representations, their abstraction levels are not that far above those found in machine code (C code is an example) [11]. Second, general-purpose processors implement very low-level computing primitives. However, the recent adoption of hardware accelerators is changing this scenario and pushing the need for optimizations and code generation at higher levels of abstractions (this also explains the renewed interest in Domain-Specific Languages).

To use such accelerators, a compiler should lower some parts of the program while raising others. For example, if an instruction in some ISA extension can perform a tiled multiplication (e.g., Intel AMX or IBM MMA), the compiler should be able to raise the code to this instruction (higher-level) representation while simultaneously lowering the remaining parts of the code. A similar situation also happens when generating code for Machine Learning (ML) engines. Thus, any robust approach for idiom recognition should be able to: (a) work on a representation that enables the coexistence of different levels of abstraction; (b) allow both raising and lowering of the program between different levels.

Fortunately, recent research has started to address these two requirements. To deal with (a), MLIR [29] enables the interplay of different languages through a common Multi-Level IR. To address (b), Chelini et al. [11] and Lücke et al. [32] proposed techniques that raise the level of abstraction.

This paper proposes a source code based approach for program matching and rewriting that leverages MLIR for lowering and raising. To achieve that, it makes two assumptions. First, it assumes the existence of MLIR implementations for both matching and replacement codes. Second, it

Listing 1. Raising dot-product and replacing by a BLAS call using SMR. Idiom and replacement are encapsulated in wrapper functions.
considers it impossible to automatically capture more program information beyond the one available at the source code, as subsequent transformations reduce the information available for analysis and optimization. Based on that, this paper claims that source code is the best abstraction level for idiom specification and a better choice to allow the non-expert programmer to design and explore his/her own idioms.

Given the discussion above, this paper describes Source Matching and Re-writing (SMR), a system that relies on a small declarative language (PAT) to match and re-write program code fragments using MLIR as a supporting framework. In SMR, the input and the idiom to be identified are lowered to their corresponding MLIR dialects (e.g., FIR [18] or CIL [12]). Then, an approach inspired by early work on tree-rewriting systems [2] is used to match the MLIR idiom pattern against the input MLIR to enable code lowering or raising.

Consider, for example, the PAT description in Listing 1 that is divided into two code sections. The first section (lines 1–6) describes the idiom code. The letter "C" at the beginning of the first section (line 1) instructs SMR that the idiom to be detected was written in the C language. In a PAT description, the idiom is encapsulated as a function (lines 2–5) where the arguments are the inputs of the idiom (in this case, dot-product). The second section (lines 6–11) describes the replacement code. It is also declared as a function (lines 8–10) with the same signature as the idiom that it intends to replace (i.e., dot-product). As detailed in the following sections, a PAT description could potentially use any language that can be compiled to MLIR and integrated with SMR. Nevertheless, inter-language/dialect rewrites are not explored in this paper. As future work, we intend to research how to leverage MLIR inter-dialect functionalities to abstract inter-language rewrites in SMR.

This paper is divided as follows. Section 2 provides a background of the techniques used in the SMR design. Section 3 gives an overview of the SMR architecture, and Section 4 details its main algorithms. Section 5 reviews other works related to this paper. Section 6 shows the experimental results, and Section 7 concludes the work.

## 2 Background

One of the central tasks in idiom recognition is the ability to pattern match the input program. Pattern matching has been extensively used to design instruction selection algorithms needed in the code generation phase of a compiler [2, 3, 19, 37].

The work proposed herein for idiom recognition (SMR) uses a similar approach as instruction selection but differs in two major aspects. First, instead of representing patterns and the input program in a low-level IR, SMR uses MLIR. This was motivated by the fact that MLIR enables a common IR structure [22] between distinct source languages. For example, in this paper, both Fortran and C source codes were lowered to their respective MLIR dialects (FIR and CIL), from which matching and re-writing can be performed. Second, contrary to instruction selection, SMR uses DAG and not tree matching (Section 3) and applies it for both control and data flow matching.

To better understand the algorithms proposed by SMR, this section covers background material on MLIR (Section 2.1) and tree-pattern matching (Section 2.2).

### 2.1 The Multi-Level Intermediate Representation

MLIR [29] is a framework with several tools for building complex and reusable compilers. Its key idea is a hybrid intermediate representation that can support different levels of abstraction. MLIR uses an interface that relies on a set of basic declarative elements [22]: Operations, Attributes, Regions, Basic Blocks, and re-writing rules. Such elements can be configured to form a dialect with a specific abstraction-level representation.

An MLIR dialect can be generated from source code with the goal of preserving high-level language information during the compilation flow. For example, C and Fortran can use MLIR to respectively translate Clang and Flang AST to the FIR [18] and CIL [12] dialects.

Although each dialect is somewhat unique, all of them must follow a common set of rules imposed by the MLIR interface [22]. The different syntax concepts of the language are implemented by configuring this interface. For example, source code if-else clauses from distinct languages can be implemented by configuring MLIR concepts of regions and operations. As discussed in Section 3, SMR relies on the common rules/structures imposed by MLIR’s interface [22] (while also allowing some configuration of its own on a dialect basis) to design a single algorithm that performs idiom matching and rewriting for both CIL and FIR inputs.

To define their structures and rewrite patterns, MLIR Operations are modeled using the Table-Gen-based [31] specification for Operations Descriptions (ODS) that is extensively used in LLVM. MLIR ODS description is eventually translated to C++ code which is then integrated into the rest of the system. Some of the basic declarative elements of MLIR are described below.

- **Operations**
  Operations in MLIR are similar to those in other IRs instructions: an operation may have input operands, generating an output operand. However, it can also contain attributes, a list of regions, and multiple output operands, among other elements.

- **Attributes**
  Attributes are used to identify specific features of operations. An operation that initializes a constant, for example, may have an attribute that defines its value, as is the case with the "std. const" operation, which uses the "value" attribute for this purpose.
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• Basic Blocks
  MLIR Basic Blocks (MLIR BBs) are defined similarly as in other IRs with a few differences. First, contrary to the classical definition in [13, 27], MLIR BBs have operations that can contain MLIR regions. Another difference is the concept of basic block arguments. These arguments abstract control-flow dependent values indicating which SSA values are available in a block.

• Regions
  MLIR regions are lists of basic blocks that may correspond to a classical reducible CFG region [13, 27], or not, depending on how the language generates its corresponding MLIR representation. For example, some languages (e.g., Fortran) implement classical reducible CFG regions (e.g., canonical loops) as an MLIR region with a single basic block, while irreducible parts of the CFG are implemented using a region with multiple basic blocks.

2.2 Automaton-based Tree-Matching
Instruction selection is a well-studied area in compiling technology [27]. During instruction selection, expression trees from a low-level IR of the program (e.g., LLVM Machine IR) are covered using a library of tree patterns. Aho et al. [2] proposed a thorough solution based on a tree-pattern matching algorithm that leverages Hoffman and O’Donnel [24] automaton string matching approach to reduce the size of the encoded tree-patterns and improve performance. Their solution was demonstrated in a tool called Twig. This paper extends [2] to enable CDG and DDG pattern matching algorithms to be used for idiom recognition in MLIR.

Figures 1 – 2 show a quick overview on how Twig’s algorithms work. First, tree-patterns Figure 1(t1)–(t3) are linearized by listing all paths from the root to a leaf. The result is a set of path-strings encoding each tree-pattern. These strings are then converted into an Automaton (Figure 2) where the transitions from states are annotated with the path-string elements, and the last state associated to the end of a path-string is marked as final. Given that strings from different tree-patterns have common prefixes, they will traverse the same set of states in the automaton, thus reducing the automaton size. For example, consider the path-string (+1r) for patterns t1 and t2 of Figure 1. In Figure 2 they share the same sequence of states (0, 1, 2, 3) finishing at state 3 which is marked final (double circled), and annotated as having recognized path string +1r from both tree-patterns t1 and t2. A tree-pattern matches if all its path-strings end in a final state.

3 An Overview of SMR and PAT
This section provides an overview of the SMR approach. It first describes PAT, a language that enables the user (or compiler developer) to specify an idiom and its corresponding replacement code. Second, it shows how PAT and SMR are integrated into a Clang/LLVM compilation flow. The reader should be attentive to the following notation, which will be used from now on: (a) pattern is the idiom code to be matched; (b) input is the program inside of which SMR will detect the idiom; and (c) replacement is the code that will replace the matched idiom within the re-written input.

As shown in Listing 2, and anticipated in Section 1, a PAT\(^1\) description is divided into two sections. In the first section (lines 1–5 of Listing 2), the language of the idiom to be matched (langA) is specified (line 1), followed by the declaration of the idiom’s wrapper function (also written in langA) that declares the arguments of the idiom pattern and their corresponding types (line 2). The pattern itself is described in the body (matchA) of the wrapper function (line 3). The second section of a PAT description (lines 5–9) contains the replacement code that will rewrite the idiom when it matches some input code fragment. Similarly, as in the idiom section, the replacement code language (langB) is also specified (line 5). The wrapper function declaration (line 6, written in langB) matches the arguments of the idiom to the variables used by the matched input fragment. In the case of an idiom match, the matched input fragment is replaced by the code in rewriteB.

The wrapper functions in the pattern and replacement sections of a PAT description serve two, and only two, purposes. First, they make the codes valid, as the front-end must be able to compile them. Second, they act as an interface between the input, pattern, and replacement codes. That said,

\(^1\)The EBNF representation of PAT is trivial, and thus we opted to present it in a descriptive format.
the wrapper function is not a part of the pattern and will never be matched, only its arguments declarations are relevant. In the matching process, SMR considers the wrapper function arguments’ order and types, as well as the function body, ignoring function’s and arguments’ names.

It is expected from the PAT file that each idiom pattern code is semantically equivalent to its respective replacement code. The author of the PAT file must ensure the correctness of such equivalence as SMR does not verify it.

PAT differs from other proposed matching languages in many ways. One remarkable differences should be highlighted, though. In contrast to approaches such as RISE [32], that use their own concepts and languages, PAT describes idiom and replacement codes using regular programming languages, thus considerably simplifying the description.

Figure 3 shows how the PAT language and the SMR approach are combined with the FIR front-end. The flow for CIL’s front-end is similar and uses the same SMR algorithm. Initially, two input files are provided to the compilation flow: (a) the input code that might be rewritten; and (b) a PAT file that has a list of idiom/replacement pairs.

As shown in Figure 3, before compiled, the PAT file is parsed, separating each pattern/replacement codes into a pair of Fortran files: idiom.f90 and replacement.f90. These files, together with input.f90, are then compiled using FIR’s front-end to generate their corresponding FIR codes.

4 The SMR Algorithm

As mentioned before, SMR relies on automaton-based DAG isomorphism to match idioms against an input program. Two major issues need to be addressed to enable that. First, although idioms are fairly small code fragments and matching their DAGs is fast, input programs can contain thousands to millions of lines of code, making it unfeasible to pattern match idioms against a whole program. To address this, SMR uses a two-phase approach that narrows down the matching search space by (a) selecting a set of candidate fragments in the input program that has a control-flow structure similar to the one in a given idiom (Section 4.1); and (b) from the filtered set of candidates, identifying those which have the same data-dependencies as the desired idiom (Section 4.2).

Moreover, although DAG matching is a GI-Complete [45] problem, idiom DDGs tend to be small and quite similar to trees, thus avoiding potential combinatorial explosions in SMR execution time. Second, depending on the problem, the number of similar idioms that can be matched could be very large, thus increasing the DAG matching algorithm’s execution time and memory usage. To optimize this task, SMR encodes idiom patterns as strings and uses automatons to compress them, similarly as proposed in Aho et al. [2]. Automatons can also be easily serialized and saved for reuse, a feature that will be available in future SMR versions. To deal with these tasks, SMR follows a compilation pipeline that implements the following sequence of operations (shown in Figure 3).

Pre/Post-processing: SMR offers a language-wise pre-processing pipeline to ease integration of new front-ends and dialects. It starts by receiving the MLIR code of the input program, the idiom patterns, and their corresponding replacements. The input and replacements may be optionally pre-processed in case they do not conform to the SMR constraints (Section 4.4). We call these tasks normalizations, as they aim to modify the code into an SMR compliant structure without altering its computation. For now, we use normalization only to peel off the idiom code, as only its body is of interest during matching. In the future, a language-wise
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pre/post-processing pipeline can also be defined to deal with other requirements that might arise with the addition of new compiler front-ends.

**CDG Matching** After pre-processing, the idiom’s MLIR code enters the CDG Matching pass to extract their CDG patterns and encode them as a set of strings. These sets are then used to build the CDG Automaton for matching. Next, SMR traverses the input MLIR code and encodes the input CDG as a set of strings. This set is then fed to the CDG Automaton to search for a control-flow match. Finally, CDG Matching outputs all candidates (input code fragments) that have a CDG identical to some idiom’s pattern CDG.

**DDG Matching** At this step, the candidate idioms resulting from CDG Matching are read by the DDG Matching pass, which builds a set of input strings for each candidate based on their MLIR representations. The DDG Matching traverses the ud-chains of the PAT file idioms, encoding them as strings to build the DDG Automaton. Finally, it feeds the set of strings generated from the input candidates to the DDG Automaton for matching.

**Rewriting** After some idiom matches an input program fragment, its corresponding MLIR code is substituted by a function call to the replacement code associated with the matched idiom pattern. A definition of such function is inserted into the input program to ensure that it is a callable function. Listing 3 shows an example of a Fortran idiom, and Listing 4, its corresponding MLIR representation. This idiom will be used in the following sections to better explain SMR, focusing particularly on the CDG/DDG Matching algorithms, as they are the two key tasks.

### 4.1 CDG Matching

As discussed before, the control structure of the generic MLIR representation is organized as a hierarchical representation of operations, regions, and basic blocks. A region in MLIR is defined by a control-flow operation called *Region Defining Operation* (RDO), and each region may contain RDOs defining nested regions. In Listing 5, for example, the first `if` operation (line 7) is an RDO that defines two regions: (a) in the first region are the operations to be performed if the condition is true (lines 8–9); and (b) in the second, the operations performed if it is false (lines 11–22). Region (b) also has a nested `if` (RDO) (line 16) defining two other regions nested in (b). Overall, the CDG Matching algorithm works as shown in Algorithm 1. First, CDGMARcfn takes the MLIR code for the input and idiom patterns (line 1). It then traverses the MLIR code of each idiom pattern (pat), building a string representation of the sequence of RDOs that define the pattern’s MLIR control-flow regions (lines 5 – 10). This way, the various idiom CDGs are stored as a set of strings (patStrings) where each string represents a sequence of control-flow regions for one idiom MLIR code. We call these strings control-strings. Each control-string originates in an RDO operation inside the MLIR code.

**Algorithm 1 Control-Dependency Graph Matching**

1: function CDGMATCH(Input, Patterns)
2:  ➔ Input: MLIR input code
3:  ➔ Patterns: set of MLIR pattern codes to match
4:  ➔ Build automaton FSM from pattern’s CDG strings
5:  patStrings ← []
6:  for each pat ∈ Patterns do
7:      ➔ pat: a single pattern code
8:          string ← STRINGFYPatCDG(pat)
9:          patStrings.append(string)
10:  end
11:  DDGAutomaton.build(patStrings)
12:  for each inStrings ∈ inStrings do
13:      patternIndexes ← CDGAutomaton.run(inString)
14:      rdo ← getRootRDO(inString)
15:      if patternIndexes ≠ [] then
16:          Candidates.insert(rdo)
17:  end
18:  return Candidates

**Algorithm 2 Data-Dependency Graph Matching**

1: function DDGMATCH(Candidates, Patterns)
2:  ➔ Candidates: MLIR operations filtered by CDG matching
3:  ➔ Patterns: List of MLIR code patterns to match
4:  ➔ Generate the DDG stringset representation of each pattern
5:  patStrings ← []
6:  for pat ∈ Patterns do
7:      ➔ pat: single pattern code
8:          ddg ← BUILDPatDDG(pat)
9:          dataSetSet ← STRINGFYPatDDG(ddg)
10:         patStringSets.append(dataStringSet)
11:  end
12:  DDGAutomaton.build(patStringSets)
13:  ➔ Build the DDG automaton to resolve stringset matching
14:  for each rdo ∈ Candidates do
15:      ➔ rdo: Control-Dependecy Graph
16:          dataSetSet ← STRINGFYInDDG(ddg)
17:          patternIndexes ← DDGAutomaton.run(dataStringSet)
18:  for each i ∈ patternIndexes do
19:      ➔ matches[i] has the matches of each pattern
20:          matches.append(rdo)
21:  return matches

---

2 Function in-lining will eventually be used here.
There, curly brackets delimit regions. An input code fragment is said to match an idiom if all elements of its control-string take the exact same sequence of states in the CDG automaton as the pattern idioms. As aforementioned, it acts only as an interface between input, pattern, and replace-ment. Therefore, the control-string starts on the first RDO of Listing 4 (line 1), that corresponds to the first if-else clause of Listing 3 (line 4). Such RDO is considered to be the RDO that defines the CDG string, which is retrieved at line 20 of Algorithm 1.

### 4.2 DDG Matching

The output of the CDG pass (Candidates) is a set containing the input code fragments (RDOs) that have a control match with at least one idiom pattern. SMR then proceeds to select from Candidates those that have a Data Dependency Graph (DDG) match to some idiom. If this happens, that idiom is said to be matched.

This task is performed by Algorithm 2 which takes as input the idiom Patterns and input Candidates (Algorithm 1 output). The goal of DDGMATCH is to model the input code fragments in Candidates and the idioms in Patterns as DDGs (Data Dependency Graphs) and verify if they are isomorphic. Input and idiom DDGs are built from their generic MLIR representations using a combination of ud-chains and regions. Also, relevant particularities of a dialect are encoded in the strings through SMR’s dialect-wise integration, allowing important attributes to be matched, and irrelevant ones, ignored.

Algorithm 2 starts by calling BuildPatDDG to build the DDG for every idiom pattern (line 9). Each idiom DDG is encoded as a set of strings (dataStringSet) by the function STRINGPATDDG (line 10). The strings in dataStringSet are linearized representations of data-flow paths in the DDG, and are called data-strings. The dataStringSet of each and all patterns are then stored together into patStringSets (line 11) so they can later be used to build the DDGAutomaton (line 14). The DDG Automaton encodes all the patStringSets data-strings, representing the DDG paths of all idioms’ patterns.
Although Algorithm 2 seems simple, it hides a complex set of tasks that considerably extends the approach originally proposed by Aho et al. in [2]. These tasks are performed by two key functions that are described in detail below: (a) DDG Building (lines 9 and 19); and (b) DDG Stringfying (lines 10 and 20).

### 4.2.1 Building DDG

One of the advantages of operating SMIR on top of a generic MLIR representation is that it can be interpreted directly as a Rooted Directed Acyclic Graph (RDAG) by using the MLIR regions and ud-chains.

The idiom in Listing 3 and its corresponding MLIR representation in Listing 5 are used here again to show the workings of Algorithm 2. To illustrate that, please refer to Figures 4 – 5, which shows the steps required to build the DDG of the MLIR code in Listing 5.

From the ud-chains shown in Listing 5, it is easy to build a DAG that serves as the basis for the final DDG. Each MLIR operation corresponds to a node in the graph, and it is labeled by a string composed of the name and relevant attributes of the operation. Note that this identification is not unique: there may be different nodes with the same string label.

To connect these nodes, we convert the MLIR ud-chains to directed edges, where the source is the MLIR operation that uses a variable, and the destination is the operation that defines that variable. Since there are operations in which the order of arguments matters (subtraction, for example), we also enumerate the outgoing edges of an operation according to the index of the input operand: the edge corresponding to the first operand is enumerated 1, the edge of the second is 2, etc. This representation is illustrated by the graph in Figure 4. By observing that graph, one can notice two problems that prevent it from being used as a representation of the Listing 5 code: control-flow incompleteness and absence of a root.

The MLIR control regions of Listing 5 are not represented in the graph of Figure 4. Therefore, there is a loss of information regarding the control structure of the code in Listing 5, making it incomplete. A possible solution for this is to assign a color to each region in Listing 5 so that all operations (graph nodes) are colored according to the region in which they are located. To represent this coloring, we identify each color with an integer ID prefixed on the string representation of the node. For example, std.const will be labeled 2_std_const, etc.

This representation is illustrated by the graph in Figure 4. By observing that graph, one can notice two problems that prevent it from being used as a representation of the Listing 5 code: control-flow incompleteness and absence of a root.
Finding Region Edges: First, the disjoint DDG graph components must be connected. To address that, let us define Region Edges, which are labeled with capital letters in Figure 5. Regions of an MLIR operation are also ordered, and therefore these edges are created alphabetically: first region has edge A, second, edge B, and so on. A region edge $R \rightarrow Y$ is created whenever there is a potential root node $Y$ that lies within a region $R$ defined by the RDO $X$. For example, in Figure 5 operation `fir.store` of (line 8 of Listing 5) is in region $A$ defined by operation `fir.if` (line 7 of Listing 5).

Thus, in Figure 5 `fir.if` to `fir.store` is a region edge. All region edges in the figure are marked as dashed lines.

Identifying DDG Root: By combining ud-chains and region edges, we attain the rooted graph of Figure 5. Since the wrapper function is not a part of the match, the outer-most `fir.if` operation will not be linked to its parent wrapper function. Thus, as long as there are no sequential RDOs in the wrapper function’s body (which is one of the constraints mentioned Section 4.4), there will be only one root RDO after linking the ud-chains and region edges. In Figure 5, such RDO is the `fir.if` root.

### 4.2.2 Building the DDG Automaton

In order to build the DDG Automaton (line 14), the pattern idioms DDG must be represented as strings. This conversion is done by the `stringifyPatDDG` method (line 10), which takes a pattern DDG and returns a set of data-strings (i.e. `patStringSet`) that are stored into `patStringSets`. After the DDG Automaton is built, the DDG of Candidates’ RDOs are extracted (line 18–19) and are converted to a set of strings by function `stringifyInDDG`, producing a `dataStringSet` (line 20), which is then fed to the automaton (line 21) for matching.

The conversion from a DDG to a `dataStringSet` is trivial. Just list all possible paths from the root to the leaves of the DDG, so that each path is composed by the concatenation of the identifiers labeled at the nodes and edges. This process is illustrated in Figure 5. The blue path data-string shows the data-dependency execution path that starts at the region defined by the root `fir.if` operation in line 7 of Listing 5 (line numbers from now on refer to that listing). From there, the path follows to the `fir.if` operation (line 16) that works as an RDO of an inner (yellow) region in Figure 5. It then proceeds to operation `stdcmpeq` (line 15) which uses constant in `std.const %c1_i32` (line 3). On the other hand, the red path (i.e. data-string) starts at the same root `fir.if` (line 7), also continues to the inner region `fir.if` (line 16), but it then diverges through region edge A, reaching the `3_fir.store` operation (line 17) of the pink region, which uses `std.const %c0_i32` (line 4). Applying this process to every path of an idiom pattern DDG will result in a set of `data-strings` (`dataStringSet`) representing the pattern.

### 4.3 Idiom Re-writing

The result of an idiom matching returns a bijection between an idiom and fragments of the input code. This bijection makes the task of idiom re-writing very simple. SMR needs only to remove from the MLIR code all the operations that can be reached from the root of the DDG of Figure 5, and then replace the DDG root operation with a call to the wrapper function of the idiom replacement code in the PAT description. In Listing 1 the dot product C idiom is replaced by a call to its replacement code which eventually calls `cblas_sdot` from the CBLAS library (line 9).

### 4.4 SMR Limitations

This first version of SMR was designed to handle only the cases of idioms that are reducible CFGs as defined in [27]. Moreover, a set of additional constraints have been adopted to accelerate the design of SMR: (a) idiom patterns may not have sequential RDOs in the wrapper function’s body (only nested RDOs). For example, if an input idiom is composed of two sequential (or non-nested) loops, it cannot be matched using a single pattern idiom. This does not prevent the user from matching the input partially by writing two pattern idioms, one for each loop; (b) Regions must contain exactly one basic block, otherwise, the DDG would have to model the possible paths between these blocks; (d) Operations must define at most one result operand. To allow more than one result would require each edge to encode not only the input operand position but also the position of the output operand being used; (e) Variadic operations are not supported. Removing such constraints is possible, but to speed up the design of the initial version of SMR, this was left as future work.

### 4.5 FIR vs. CIL

As aforementioned, the lowering process from source code to MLIR depends on the choices of the dialect designer. Hence, similar semantic clauses can be lowered in different ways. An example of such is the difference between CIL and FIR regarding the lowering of `if-else` clauses. While FIR directly handles the clause with regions, CIL uses the traditional basic blocks method with branching comparison operations, generating a lower level MLIR representation than FIR. That said, FIR can still fall into the same scenario when unstructured code or branching operations are in the input code. If a Fortran `EXIT` statement is used within a loop, for example, the IR generated by such loop falls directly into an MLIR basic block representation. The same happens when dealing with `SELECT CASE` statements. In most other aspects, CIL and FIR are quite similar. However, while FIR is currently well supported by the community, CIL has not received any official contributions since it was presented to the LLVM community, rendering it a more crude MLIR dialect when compared to FIR. Regardless, at the writing of this paper, and to the best of our knowledge, CIL is the only available MLIR dialect representation for C/C++.
5 Related Work

Pattern matching techniques have been used for decades to implement compiler optimizations. While early research mainly focused on IR pattern matching for code generation [2, 3, 19, 37], recent works explored more complex patterns that include program control flow [10, 11, 21, 32]. LLVM already provides a pattern matching mechanism, which has been used in [10] to replace computation kernels such as GEMM with optimized implementations. Although their approach results in good speedups, it is not very flexible. Every new kernel (i.e., idiom) they introduce needs to be hard-coded into the compiler. MLIR offers a more advanced and generic pattern matching and rewriting tool [29] based on a specific MLIR dialect known as the Pattern Descriptor Language (PDL) and a DAG Rewriter mechanism. PDL provides a declarative description of IR patterns and their replacements while also using the generic representation of MLIR to enable that to other MLIR dialects. PDL works quite well in the case of simple patterns, but it is not yet possible to use it to describe more complex idioms such as matrix multiplications [43]. In fact, the generic representation of MLIR is very low-level, and algorithms relying on advanced control structures are complex to express in it. On the other hand, dedicated MLIR dialects can be used to capture idioms for optimization. For example, Uday Bondhugula [9] has matched GEMM idioms and replaced them with BLAS calls to improve performance. But similarly, as in [10] matching/ replacement is hard-coded inside the compiler.

Several works try to expand LLVM and MLIR pattern matching through domain-specific languages to ease the matching of complex idioms by using custom functional languages [11, 32] or a constraint-based language [21]. For all those approaches, the idiom descriptions are synthesized as LLVM IR or MLIR passes that perform pattern matching. The fundamental difference between those works is that Chelini and al. use pattern matching to raise the abstraction level of the intermediate representation of general-purpose languages to allow domain-specific optimizations, while Lücke and al. mostly focus on simplifying pattern matching for a domain-specific IR. On the performance side, Chelini and al. already demonstrate their approach for linear algebra operations against standard compilation optimizations and polyhedral optimizations. All such approaches clearly allow a more compact way to match and rewrite idioms. Nevertheless, they require re-compiling the compiler and/or are not very friendly to express idioms as source code is in SMR, two undesirable features when targeting idiom exploration.

Barthels and al. [6] explore the automatic rewriting of linear algebra problems from high-level representations (Julia, Eigen, or Matlab) using pattern matching and rewriting. Their work uses the mathematical properties of linear algebra operations and data structures to derive efficient implementations. Although they clearly demonstrate the potential of raising, their approach only works when the target program uses high-level function calls to algebraic operations.

Similar to SMR, the XARK compiler [4] uses a two-phase approach to match idioms. However, SMR uses automate string matching, which is more efficient than matching an IR graph representation directly, and starts by analyzing the CDG to quickly eliminate non-relevant idioms. Additionally, XARK reduces idioms expressiveness more than SMR since it requires linearizing the accesses to multidimensional arrays.

Polly [23] focuses on polyhedral loop transformations, but also uses pattern matching in some cases. Polygeist [33] is a C front-end for the MLIR Affine dialect which was not released in time to be used by this work.

Verified Lifting [26] uses a formal verification approach to perform pattern matching and higher-level rewriting. Their approach showed good results but it is specialized to stencil codes and, in some cases, need to include user annotations to ensure the correct rewrite.

6 Experimental Results

This paper aims to propose and validate SMR, a programmer-friendly approach for idiom matching and rewriting. Contrary to other works [11][9], we do not seek to evaluate the performance of the rewritten programs for other established polyhedral-based techniques, as this has already been explored [11]. With this in mind, three sets of experiments have been designed to evaluate SMR. First, a set of Fortran programs was used to validate the correctness of the rewritten code by demonstrating the expected speedups. Fortran was selected because its corresponding MLIR dialect (FIR) is quite stable and well maintained by the community, while C’s dialect (CIL) is still in a very brittle state. In the second set of experiments, the impact of SMR matching/replacement on the standard FIR compilation time was measured. Finally, the goal of the last set of experiments was to evaluate the ability of SMR to match another language dialect (C/CIL). Evaluation of SMR’s potential to capture more generic patterns was left as future work.

All experiments were performed using a dual Intel Xeon Silver 4208 CPU @ 2.10GHz with 16 cores total and 191 GiB of RAM running Ubuntu 18.04. As for the software tool-chain, the following commits/versions have been used: (a) Flang (FIR) commit 8abdc290 [41]; (b) CIL commit 195acc3 [40]; (c) LLVM/MLIR commit 1fdec59 [42]; (d) OpenBLAS version 0.2.20 [44]; and (e) GFortran version 4.8.5. Experiments used programs from Fortran Polybench 1.0 benchmark [34], and a set of 6 large well-known C programs from different application domains (top labels of Table 1) that perform intense arithmetic computations, extracted using the Angha tool [14]. All experiments were executed following up the benchmark execution guidelines. They used standard reference inputs and were executed 5 times showing small execution time variations (≤ 5%). SMR has detected no false-positive idioms in all experiments.
In the first experiment, a set of idioms targeting Fortran double-precision BLAS kernels have been designed using the PAT language and applied to Fortran Polybench programs for matching. Idioms were substituted by the corresponding Fortran BLAS calls, and execution times were measured with the LARGE_DATASET option (Figure 6). As shown in the figure, the performance of the Flang version used in this experiment lags behind GFortran. When using the FIR front-end together with SMR idiom detection and Fortran BLAS replacement (SMR+BLAS, blue bar), all programs showed speed-ups, ranging from 5x to 295x. For some programs, SMR could not replace the kernel with a single BLAS call, either because there is no matching BLAS call for the kernel or because it does not meet SMR restrictions. In such cases, partial replacements by multiple BLAS calls occurred. This resulted in speed-ups, as in the case of 2mm (replaced by two GEMMs), atax (partially replaced by two GEMVs) and b1gc (partially replaced by GEMVs calls). Other programs from the benchmark were neither fully nor partially rewritten (e.g. syrk), given they are composed by sequences of RDOs, an SMR restriction, and could not be separated into multiple BLAS calls. As discussed before, this restriction is a solvable issue, and work is underway to address it.

In the second set of experiments, execution times for Fortran Polybench programs were measured using FIR compilation with and without SMR+BLAS (Figure 7). As shown in the figure, the compilation overhead ranged from 52 ms to 125 ms. The reader should notice that SMR+BLAS compiles and builds the automata for each set of idioms in a PAT file. This is not required, though. In the future, we intend to compile the PAT file once and save the idioms’ automata for reuse, thus eliminating 60% – 85% of this overhead.

In the final set of experiments, 9 idioms associated with C BLAS calls were used with the CIL front-end to perform idiom matching on 6 C programs. Program re-writing was skipped due to the unstable state of the CIL front-end. Table 1 shows the number of idiom occurrences detected per input program. Overall, 22 idioms occurrences were detected in all six programs, with Darknet and Nekrs matching 9 occurrences each, respectively using 5 and 4 distinct idioms. As a comparison, Polly v13.0.0 was only able to match the gemm idiom: 1 occurrence in Darknet and 3 in Nekrs. We also confirmed that PDL was not able to handle those idioms since it does not yet support regions [35].

### 7 Conclusions

This paper proposes SMR, a source-code and MLIR based idiom matching and re-writing approach. By using MLIR generality, SMR could match both Fortran and C programs through their corresponding dialects (FIR and CIL). In FIR’s case, it was also able to optimize benchmarks through code rewriting. Future extensions will address the SMR constraints listed above, enable inter-language replacement and matching of novel accelerated ISA extensions and library calls, and replacement with high-level operations from other MLIR dialects.

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**Figure 6.** Polybench running time after BLAS replacement.

**Figure 7.** FIR compilation time with/without SMR+BLAS.

| Idiom  | Darknet [3] | Cello [25] | Explort [30] | Fmpeg [64] | Hping3 [1] | Nekrs [17] | Total |
|--------|-------------|------------|-------------|------------|------------|------------|-------|
| saxpy  | 1           | 1          | 1           | 1          | 1          | 1          | 9     |
| scoppy | 1           | 1          | 1           | 1          | 1          | 1          | 9     |
| sdot   | 1           | 1          | 2           | 1          | 2          | 2          | 9     |
| sgemm  | 4           | 1          | 4           | 4          | 4          | 4          | 9     |
| scall  | 2           |            | 2           |            |            |            | 3     |
| ddot   | 1           | 1          | 2           | 4          |            |            | 9     |
| dgemm  | 1           |            | 3           | 4          |            |            | 9     |
| dgemm  | 1           |            | 1           |            |            |            | 3     |

**Table 1.** Matching with CIL and CBLAS idioms.

3Due to the differences in execution times, y-axes were broken, and programs separated into two groups.
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1 Artifact Appendix

1.1 Abstract

SMR’s artifact reproduces the results presented in Section 6, thus validating the algorithms’ aspects discussed throughout the paper. It is composed of a Docker container with bash scripts that reproduce the paper’s results (Figure 6 and Figure 7). A Linux system with an up-to-date Docker installation and at least 20G of disk memory is required. One of the results (Table 1) is not entirely reproducible due to its computational heft, but can be partially executed.

1.2 Artifact check-list (meta-information)

- **Algorithm**: Source Matching and Rewriting (SMR), a source code pattern matching and rewriting algorithm based on the MLIR framework.
- **Program**: Kernels utilized in the artifact are from PolyBench/Fortran 1.0 benchmark (already included).
- **Data set**: LARGE_DATASET mode predefined in PolyBench/Fortran 1.0.
- **Run-time environment**: Linux system supported by LLVM with up-to-date Docker support (Ubuntu 18 or greater is recommended).
- **Output**: PDF files replicating Figure 6 and Figure 7, which show SMR rewrite optimization speedups and compilation overhead.
- **Disk space required**: ≈ 20 gigabytes of free space.
- **Time to run experiments**: ≈ 20 minutes.
- **Publicly available**: Yes, via GitLab and Docker hub.

1.3 Description

1.3.1 How is it delivered?

- A container with all required tools can be downloaded with docker pull sitio/smr-artifact
- A Dockerfile and all other requirements to build the container can be found at the artifact’s repository [5].

1.3.2 Hardware dependencies:

- Any platform supported by LLVM [15]

1.3.3 Software dependencies: All required binaries are contained within the docker container.

- clang, cmake, flang, gfortran and libopenblas-dev can be installed via Ubuntu’s package manager.
- FIR is available at f18-llvm-project/fir-dev@8abd29 [18].
- MLIR 11 is available at llvm-project/tree/release/11.x [42].
- PolyBench/Fortran is available at www.cs.colostate.edu [34].
- CIL is available at compiler-tree-technologies/cil [12]
- SMR is available at parlab/pat-compiler [7].

1.4 Experiment workflow

Bash scripts can be used to reproduce the experiments:

- execution_times.sh to reproduce Figure 6
- compilation_times.sh to reproduce Figure 7

- angha_matches.sh to partially reproduce Table 1

To demonstrate correctness, an extra script (validate.sh) can be used to compare PolyBench reference values against the rewrites applied by SMR in the execution_times.sh experiment.

Steps to reproduce the experiments:

- docker pull sitio/smr-artifact
- docker run -it -name smr sitio/smr-artifact
- cd /root/smr-artifact
- bash compilation_times.sh
- bash execution_times.sh
- bash angha_matches.sh
- bash validate.sh

After executing the steps above, two PDF files will be generated in /root/smr-artifact: compilation_times.pdf and execution_times.pdf. In order to visualize the graphs, copy the generated PDFs files from the container to the host machine with docker cp and open them with any PDF viewer.

Results for the angha_matches.sh and validate.sh scripts are exhibited directly on stdout. The first will list how many matches were found for each C file in the angha folder, and the latter will log if the SMRs results are within and acceptable relative error margin.

1.5 Evaluation and expected results

Experiment compilation_times.sh shows the overhead added by the entire SMR rewriting process. The column representing SMR is expected to be taller (slower) in every kernel, how much taller will depend of the host machine.

Experiment execution_times.sh quantifies the improvement achieved by rewriting the traditional PolyBench kernels by its BLAS counterparts using SMR. This experiment can also vary depending on the host machine, however, times for gFortran and Flang binaries should always be substantially larger when compared with SMR and BLAS times.

Experiment angha_matches.sh shows SMR functioning with the CIL dialect and frontend, reiterating its flexibility for multiple source languages. However, this experiment is only partially reproduced in the artifact: the web crawling, code reconstruction and input code filtering steps are all left out due to their computational demanding nature, which would take several hours to reproduce.

The validation.sh script checks correctness of the rewrites performed by SMR with BLAS in the execution_times.sh experiment. The validation consists of a relative error check which tolerates a margin of 0.00001% from PolyBench reference values. Any result that exceeds the threshold will be printed as an error in stdout.