Analogy-Making as a Core Primitive in the Software Engineering Toolbox

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Abstract
An analogy is an identification of structural similarities and correspondences between two objects. Computational models of analogy making have been studied extensively in the field of cognitive science to better understand high-level human cognition. For instance, Melanie Mitchell and Douglas Hofstadter sought to better understand high-level perception by developing the Copycat algorithm for completing analogies between letter sequences. In this paper, we argue that analogy making should be seen as a core primitive in software engineering. We motivate this argument by showing how complex software engineering problems such as program understanding and source-code transformation learning can be reduced to an instance of the analogy-making problem. We demonstrate this idea using Sifter, a new analogy-making algorithm suitable for software engineering applications that adapts and extends ideas from Copycat. In particular, Sifter reduces analogy-making to searching for a sequence of update rule applications. Sifter uses a novel representation for mathematical structures capable of effectively representing the wide variety of information embedded in software. We conclude by listing major areas of future work for Sifter and analogy-making in software engineering.

1 Introduction
An analogy is defined as “a comparison between two objects, or systems of objects, that highlights respects in which they are thought to be similar” [5]. Humans make complex, fluid analogies in everyday communication. For example, a recent CNN headline [10] states that “the ‘beating hearts’ of these pulsating stars create music to astronomers’ ears,” noting correspondences between pulsation of stars, the beating of a heart, and the rhythm of music. In fact, analogy-making is such a fundamental skill that a major portion of the original SAT exam was dedicated to having test-takers complete analogies such as “Paltry is to significance as X is to Y.”

Analogies have been shown to be a useful instructional tool for improving student learning [25]. For instance, analogies are frequently used to explain concepts in physics [9, 64], geography [54], mathematics [69, 70], and computer science [17, 18, 21, 26, 32, 46, 75]. For example, a professor of an introductory computer science course might explain the concept of a program by forming an analogy between the execution of a program by a computer and the following of a recipe by a cook, likening steps in a recipe to statements in a computer program, ingredients in a recipe to resources in a program or user inputs — analogies are not always unambiguous.

The important role of analogy-making in high-level cognition has been argued by many researchers in both cognitive science and computer science [19, 20, 52]. Professor Douglas Hofstadter and his Fluid Analogies Reasoning Group (FARG) [33, 34] argue that humans are constantly making analogies, comparing features of their current situation with previously-encountered scenarios to decide what to do next. To study the analogy-making process in more detail, they have developed computational models of analogy making. One such algorithm, Copycat [35], can complete analogies over strings (Section 2). Copycat can answer questions such as “abc is to abd as efg is to what?”

This paper explores the role of analogy-making in software engineering (SE). We argue that a number of SE problems can be framed as analogy-making. We introduce a dedicated analogy-making algorithm, Sifter, which can be used as a core primitive to solve such SE problems. We believe that future research on analogy-making algorithms like Sifter will solidify analogy-making as a core primitive in the software engineering toolbox.
The first application of analogy-making we consider is the problem of program understanding (Section 3.1). One fundamental way that humans understand new source code is by analogy to source code that they already understand. As an example, consider a programmer who has become familiar with the source code of the Bourne-Again Shell (bash) [7] and now wishes to add a new feature to the Friendly Interactive Shell (fish) [6]. A reasonable first step would be to read the source code of fish and attempt to identify functions in its implementation that play a similar role to more familiar functions in the implementation of bash. In other words, the programmer will form an analogy between the two source code repositories and use the analogy to determine where to make the desired modification.

The second application of analogy-making we consider is the problem of generalizing a source code optimization (Section 3.2). As an example, consider a scenario where an optimized matrix multiplication implementation should be used when the matrix sizes satisfy certain conditions. After seeing a small number of code corrections replacing the sub-optimal multiplication routine with the optimized one, most trained programmers would begin to internalize the pattern. Consequently, when they come across new code that can be optimized they would be able to form an analogy to those corrections and modify the code to use the optimized version.

Here, the programmer needs to form an analogy between pairs of programs, before and after the transformation, for example stating that “all of the sub-optimal code calls matrix multiplication routine X with inputs like Y, and the corresponding optimized code replaces X with Z.”

Finally, the third application of analogy-making we consider is the problem of API migration (Section 3.3). As an example, consider the scenario where a library that has updated its public interface to change its error codes and remove a now-redundant parameter from each relevant function. After updating a small number of functions to use the new API, a programmer might quickly realize that all of the changes they need to make are “fundamentally the same:” lookup the new error code in the documentation, switch the old error code for the new wherever it is checked for, and then remove the redundant parameter. The programmer has, thus, formed an analogy between the different edits, which they can use to quickly migrate similar code elsewhere in the project.

In all of these examples, and many more discussed in Section 3.4, the programmer reasons about the source code and relations between different parts of the source code to form an analogy highlighting the fundamental similarities between a set of examples.

Motivated by this, we developed Sifter, an analogy-making algorithm suitable for analogy-making on source code (Section 4). Sifter takes as input a description of the source code in a mathematical format using arbitrary relations. This description is expressive enough to represent syntactic as well as semantic information about the source code. Sifter can also take as input and reference in its analogies non-code sources like documentation. The design of Sifter is principled and ultimately reduced the analogy-making problem to that of a search over possible rule applications for rewriting a workspace described as a triplet structure.

We believe that Sifter can form a powerful primitive in the SE toolbox. Sifter is general enough to handle arbitrary relations, and, hence, can make analogies synthesizing semantic, syntactic, and natural-language information. Sifter’s output is explainable, as it internally solves analogies by symbolic manipulation and identifying corresponding facts. Finally, by reducing many distinct problems to Sifter, improvements to it will directly pay dividends across a wide number of applications. The implementation of Sifter is available at https://github.com/95616ARG/sifter.

2 Analogy Making over Strings

This section explains the notion of analogy making. Following Hofstadter, we focus first on analogies between letter strings, sequences of letters and symbols. Section 2.1 then describes analogy completion. We end by describing Copycat (Section 2.2), a system from prior work for completing analogies involving such letter strings, which influenced the design of the Sifter system introduced in this paper.

Informally, analogy making over strings entails determining in what respects two given strings are similar. For instance, consider the strings abc and efg. For the string abc, we have that the second letter is the successor in alphabetical order of the first, and the third is the successor of the second. The exact same property holds for the string efg.

More formally, analogy making entails inferring properties that hold for both strings. Consider the binary relation NextTo, where NextTo(x, y) implies that the letter x is the left of the letter y in a given string. For the string abc, we have NextTo(a, b) and NextTo(b, c). Furthermore, consider the binary relation LetterSuccessor where LetterSuccessor(x, y) holds if the letter y is the successor of letter x in alphabetical order. In this example, we have LetterSuccessor(a, b), LetterSuccessor(b, c), LetterSuccessor(e, f), and so on. Using these two relations, we can state that the elements S = \{a, b, c\} of the string abc satisfy the following property \(\phi\): \(\forall x, y \in S. \text{NextTo}(x, y) \implies \text{LetterSuccessor}(x, y)\). We see that the elements of the string efg satisfy this same property. Hence we have formed a meaningful analogy between abc and efg.

However, not all analogies can be succinctly expressed via a first-order logic formula such as \(\phi\). Consider making an analogy between the strings abc and gfe. In this case, the elements of abc satisfy \(\phi\), but the elements of gfe satisfy the property \(\phi’\): \(\forall x, y \in S. \text{NextTo}(x, y) \implies \text{LetterSuccessor}(y, x)\). In particular, the order of the arguments to LetterSuccessor in \(\phi\) and \(\phi’\) are different. Intuitively, the property \(\phi’\) reads the string from right to left, instead of left to right. Consequently, the analogy maker needs to be
able to express such “slips”: the strings abc and gfe satisfy almost the same property, except that one reads the string from left to right and the other from right to left.

Such properties can become even more difficult to state in a first-order logic notation when grouping is involved. Consider making an analogy between the strings aaabbc and ddddcccbba. There are many reasonable analogies between these strings. For example, we might associate the group of letters aaaa in the first string with a in the second string, noting that all of the letters in the first and the one letter in the second satisfy the unary IsLetterA predicate. Alternatively, we might associate aaaa in the first string with dddd in the second string, as they are both groups of a single repeated letter occurring at the start of their corresponding string. In particular, the strength of an analogy lies less in the number of features the two strings have in common than in the overlap of relational structure between the two strings [24]. Regardless, it is not clear how one might naturally express the fundamental properties that these two strings share in a standard logic notation. Instead, as humans we might be tempted to communicate the shared property via a drawing like the following:

In this drawing, G1 through G_n represent the groups of letters in each string. Each group is made up of letters x_1, ..., x_m, which all satisfy the LetterSame relation with each other. The groups themselves then have some shared binary relation r_i, relating them. For example, in aaabbc, we might have aaaa take the place of G_1 and r_1(x,y) = LetterSuccessor(x,y) ∧ NextTo(x,y), while in ddddcccbba we might have a take the place of G_1 with r_1(x,y) = LetterSuccessor(x,y) ∧ NextTo(y,x). Note again that we have flipped the order in the latter NextTo, intuitively to read the second string from right-to-left.

Such drawings motivate an alternate way of thinking about analogy making. In this interpretation, analogy-making involves defining an abstract string description that can be instantiated to produce the given strings. As we have seen, such an abstract string description needs to be general enough to handle all of the complex grouping and slipping that can occur in such letter string analogies.

2.1 Analogy Completion on Transformations

One particularly interesting use-case for analogy-making is to make analogies between pairs of objects, such as a state before and after some transformation. For example, given the pairs abc→abd and efg→efh, we can compare the two pairs, forming an analogy which might be represented by an abstraction like:

In this scenario, the analogy-making process involves learning an abstract representation of the transformation performed in each pair of strings. We have said that both pairs of strings correspond to each other because they both share the properties shown in this diagram.

With such a representation of a transformation, one can also perform Analogy Completion, like in the original SAT exam. For example, given two example pairs of strings abc→abd and efg→efh and a prompt ijk→?, we can ask for a completion of the analogy, a value which can replace the ? to make all three pairs form a strong analogy. In this case, one completion would be the string ijk.

We can find such a completion by first constructing an analogy between the examples abc→abd and efg→efh to form the abstract string drawn above, then we can start to form an analogy with the examples and the prompt ijk, from which we might infer that i is an instance of x_1, j an instance of x_2, and k an instance of x_3 in the abstract string. We can then infer that there should be some letters corresponding to y_1, y_2, y_3, and that they should satisfy the properties in the drawing. From the drawing, then, we have LetterSame(i, y_1), hence we should have y_1 = 1; then LetterSuccessor(y_1 = 1, y_2) to get y_2 = j; and finally LetterSuccessor(k, y_3) to get y_3 = 1, completing the analogy with the desired string ijk.

2.2 The Copycat Algorithm

The Copycat algorithm [35] was developed to solve such string analogy-completion problems. Copycat’s architecture is similar to that of a blackboard-based automated theorem prover. It consists of a workspace, or blackboard, which initially contains only the example pairs (such as abc→abd) and a prompt (such as ijk→?). This workspace is modified by a set of codelets, which are small programs that operate on the workspace. These codelets can make a variety of modifications to the workspace. Some codelets may group letters together, like the aaaa in aaabbc. Other codelets identify bonds, or relational facts about symbols, for example noting that LetterSuccessor(a,b) is true. Still further codelets can build bridges between symbols, representing the determined correspondences in the analogy. Once a consistent analogy among the examples and prompt is made, a purpose-built solver is used to construct the corresponding completion.

The resulting analogy is determined by the order and type of codelets used, along with where each one “focuses.” The behavior of the codelets is controlled by what is essentially a sophisticated set of heuristics wrapped into a structure known as a Slipnet.
3 Applications of Analogy Makers in SE

In this section, we demonstrate the use of our analogy maker Sifter by applying it to three SE problems and list specific challenges addressed by Sifter. A large number of further applications are then discussed in Section 3.4. We defer the description of the design of Sifter to Section 4.

3.1 Comparative Program Understanding

Suppose you are a programmer who is quite familiar with the implementation (source code) of bash [7], and you would like to add a new feature to a different shell, such as fish [6]. Because you have been adding features to the bash shell for many years, you may know exactly which function(s) to modify in the source code of bash to add the desired feature. However, being new to the source code of fish, you face a significant challenge understanding the implementation of fish before you can even begin writing your new feature.

You might start by reading the source code of fish, looking for functions and objects that play similar roles to ones you are more familiar with in bash. This is fundamentally an analogy-making problem, where we are attempting to form an analogy between the source code of bash (which we are familiar with) and that of fish (which we are not).

This problem is similar to that of forming letter analogies in Section 2, where, given the strings abc and efg, we found that b and f corresponded to each other. Here, abc is instead the source code of bash, while efg is the source code of fish. b and f are likewise functions in bash and that which play similar roles.

Sifter is designed to make such analogies on programs. We first load both source repositories into Sifter, then ask it to identify an analogy between the two. This analogy will effectively be a mapping between the repositories, identifying functions, classes, and statements in the source code of bash with those in the source code of fish. Such an analogy can form an invaluable guide, allowing you to look up, for example, the function in fish which Sifter thinks plays the most similar role to the one you would have modified in bash.

Challenge 1: Compositional Structure of Programs

Program source-code relies heavily on compositional structure. For example, the meaning and interpretation of any function depends not only on its immediate body, but also on the body of all functions that it calls, and the functions they call, and so forth. On the other hand, the role a function plays in a large piece of software usually depends on the functions that call it.

Sifter can make use of this compositional structure, by building on top of analogies it has already made. For example, in Figure 1 we have provided snippets of the source code of the bash and fish shells. Sifter begins by associating the functions cd_builtin (B1) and builtin_cd (F1) because of their similar names and signatures. Then, once it has decided that these two functions correspond, Sifter can start to make inferences that the places where they are used are likely to correspond as well. For example, it might note that both shellBuiltins (B3) and builtinData (F2) contain a struct with a field of cd_builtin or builtin_cd respectively, and mark those two objects as corresponding in the analogy. It can similarly infer that functions using those objects, such as builtin_address_internal (B4) in bash and builtin_lookup (F3) in fish, correspond.

In this way, Sifter can build up Analogies made about parts of the program to begin to make stronger and stronger inferences about how the rest of the source code corresponds. Although we have not demonstrated it in this example, Sifter can also make analogies in a top-down fashion, e.g., by starting at the main function in both programs, or by alternating between such top-down and bottom-up strategies. Notably, such compositional structure was not needed to find analogies between the letter groups in Section 2, demonstrating how analogy-making on programs can be richer and more challenging than on letter strings.

Challenge 2: Multiple Syntactic Representations of Programs

Another challenge with analogy-making on programs is that semantically equivalent programs can have multiple syntactic representations. For example, functions can be inlined or if/else conditionals can be inverted. Sifter can handle such scenarios by applying transformation rules, such as function inlining, to transform either source repository it is given. Sifter searches through different representations of each source repository until it finds ones that are amenable to forming strong analogies.

Because letter strings do not have an assumed semantics, there is no equivalent notion of semantics-preserving transformation rules for the examples in Section 2. However, operationally, the process of grouping letters, e.g., in aaabbcc, can be seen as such a transformation, where the internal representation of the individual letters a, a, and a are transformed into a single group of letters aaa.

3.2 Generalizing Program Transformations from Examples

Suppose we have a linear algebra library with multiple General Matrix Multiply (GEMM) routines for computing matrix multiplications. Some routines, such as gemm_large, are optimized for the case where the input matrices are relatively large, say with over 1,000 rows each, while others like gemm_skinny are optimized for “skinny” inputs, e.g., where the inner dimension is the size of either of the outer dimensions.

For a particular team working on a particular codebase, it may be the case that most matrices are usually quite large and so gemm_large might become the de-facto routine that developers use in new code without thinking too deeply about matrix sizes, or simply used due to copy and paste
from existing code. While this might be a reasonable default for this team, it is likely the case that some matrices in a program are better suited for gemm_skinny — in that case, the instinctive default would be sub-optimal, and another programmer might notice during code review that gemm_skinny would be a better choice.

The question we would like to consider is: given two example code pairs where gemm_large has been transformed into gemm_skinny, can we automatically optimize new code in the same manner? This is fundamentally an analogy problem, where we would like to compare the pairs of pre- and post-replacement code to learn the core transformation that explains all of them. We can then use this analogy to infer, for some new sub-optimal code, the corresponding optimized code. This is similar to completing the analogy abc→abd, efg→efh, ijk→? in Section 2.1.

This scenario is shown in Figure 2. The first two rows in that figure show pairs of examples of the desired source code transformation provided to Sifter, which play the same role as abc→abd and efg→efh in Section 2.1. The code in the left-hand column is sub-optimal because it calls gemm_large on matrices with dimensions that would be better suited for gemm_skinny. The code in the right-hand column has been optimized by replacing the call to gemm_large with a call to gemm_skinny. In the third row of Figure 2, we have provided Sifter with a new piece of code on the left and ask it to complete the analogy, i.e., produce the corresponding piece of code on the right that makes all three rows the most similar. This plays the same role as the efg→? input in the letter analogy example. The code produced by Sifter is shown on the bottom right of Figure 2 in green, where we see it has correctly replaced the call to gemm_large with a call to gemm_skinny.

**Challenge 3: Avoiding False Positives**

Sifter is forming an analogy between the rows in Figure 2, including between the before code on the left-hand side. In Figure 2, for example, Sifter has noted as part of its analogy that all of the left-hand code snippets call the function gemm_large with the last argument at least twice that of the second-to-last argument. This behavior can be thought of as learning to recognize code that can be optimized, and can be used to avoid false positives. For example, suppose instead of the sub-optimal prompt code given in the bottom-left of Figure 2, we gave Sifter the code:

1. assert(k > 0);
2. int outer = k * 10;
3. int inner = k * 10;
4. read_mat(outer, inner, &A);
5. read_mat(inner, outer, &B);
6. gemm_large(A, B, &C, outer, inner, outer);

In that scenario, Sifter would attempt to form an analogy between this code and the example before-transformation code on the left-hand side of the first two rows of Figure 2. While it may succeed in proposing an analogy, Sifter will note as part of its output that the analogy is not particularly strong. This is because this new code does not share the property that the last argument to gemm_large is at least twice that of the second-to-last one.

If examples of already-optimized code are available, given a new instance Sifter can also try to form an analogy using these negative examples. A threshold can be set based on a comparison with the negative vs. positive examples to determine whether to apply the transformation.

**Challenge 4: Using Semantic Information**

Recognizing sub-optimal code relies on semantic information about the possible values a variable can take on. In particular, we only want to apply the transformation when the inner matrix dimension is at most half the size of the outer dimensions. This would cause difficulty for syntax-based tools like GetAFix [4]. However, Sifter takes as input an arbitrary structure consisting of symbols and relations between the symbols. This means that, in addition to providing the source code, we can annotate the structure representing the source code with the results of a program analyzer, which...
allows us to include information about semantic properties of the code. In this example, we can annotate the structure with relations that some variable is always at least twice that of another. The analogy-making algorithm that forms the core of Sifter is entirely indifferent to the underlying relations being used, and will use such semantic relations to form analogies just like it would more syntactic relationships describing the source code.

3.3 API Migration

For the final task, consider the two versions of a camera library documented in Figure 3, which has been updated to automatically determine the resolution to use as well as changed the error codes. Suppose you have a program that includes in its analogy semantic information like the fact that all of the outer dimensions in the examples are at least twice that of the inner dimensions, helping it to avoid false positives.

Figure 2. Optimizing program source code with Sifter. The left column shows before the optimization and the right column after the optimization. The first two lines are the examples given to Sifter, while the green code is generated by Sifter to complete the analogy for the last line. Sifter includes in its analogy semantic information like the fact that all of the outer dimensions in the examples are at least twice that of the inner dimensions, helping it to avoid false positives.

Challenge 5: Using Documentation in Analogies

There is one particularly pressing challenge we wish to highlight here: given only these code pairs, there is no reasonable way to complete this analogy, because it depends on knowing the new error code for record_frame, which did not appear in any of the examples. To address this, we can give Sifter the before/after documentation in addition to just the source code. Again, because Sifter takes any structure as input, we can encode documentation just as easily as we can encode source code. Then, in making analogies, Sifter can refer to the documentation and include looking up in the documentation as part of the analogy.

Challenge 6: Using DNN Models in Analogy-Making

Once we begin involving arbitrary text (e.g., in documentation), we need to start being able to handle fuzziness inherent in human languages. For example, in the documentation for the first two functions, the corresponding error message could be found with a relatively simple search, because it was prefaced with "On error . . . returns." However, for the record_frame function, the corresponding sentence uses "failure" instead of "error," which could cause Sifter to lose confidence in its analogy. To help increase Sifter’s confidence in its analogy and guide it towards the right answer, we can use existing natural-language tools such as DNN-based sentiment analysis models. These models take a paragraph,
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Just like with the results of a program analyzer, we can annotation, which has been addressed by code-clone detection [88].

Future software engineering applications

A smart editor may make analogies between the user’s current editor state and a corpus of code samples to suggest structural code completions, similar to those accomplished using large code corpuses like Aroma [45] or more local history such as Blue Pencil [51]. Because our approach does not rely on AST parsing (see Section 5.1), we can use analogies to automatically improve tooling (error messages, linting, suggestions, bug finding, etc.) for nascent and domain-specific languages (DSLs) that may not yet have a formal grammar [8, 60].

Figure 3. API documentation before after migration for the camera API. This documentation is provided to Sifter to complete the analogy shown in Figure 4.

Figure 4. API migration with Sifter. The left (right) column shows before (after) the migration. The first two rows are the input to Sifter, while the green code is generated by Sifter to complete the analogy for the last row. Sifter was also given as input the API documentation pair from Figure 3, which is where it looks to find the new error code used in the generated code.

| 1 | # CameraLib v1.0 |
|---|---|
| 2 | `record_video(buffer, buffer_size, resolution)` |
| 3 | Records video from the main camera into ‘buffer’ until ‘buffer_size’ bytes are reached. On error returns -3. |
| 4 | `record_audio(buffer, buffer_size, resolution)` |
| 5 | Uses the main camera’s microphone to record audio into ‘buffer’ until ‘buffer_size’ bytes have been recorded. On error returns -5. |
| 6 | `record_frame(buffer, buffer_size, resolution)` |
| 7 | Uses the main camera to record a single image to ‘buffer’. On failure returns -3. |

| 1 | # CameraLib v2.0 |
|---|---|
| 2 | `record_video(buffer, buffer_size)` |
| 3 | Records video from the main camera into ‘buffer’ until ‘buffer_size’ bytes are reached. On error returns -4. |
| 4 | `record_audio(buffer, buffer_size)` |
| 5 | Uses the main camera’s microphone to record audio into ‘buffer’ until ‘buffer_size’ bytes have been recorded. On error returns -2. |
| 6 | `record_frame(buffer, buffer_size)` |
| 7 | Uses the main camera to record a single image to ‘buffer’. Automatically sets the resolution to fit in ‘buffer_size’. On failure returns -6. |

| 1 | ... |
|---|---|
| 2 | `void try_record_video()` |
| 3 | `int` result = record_video(buffer, BUFFER_SIZE, RES_AUTO); |
| 4 | `if` (result == -1) |
| 5 | `printf("Could not record video.\n"));` |
| 6 | `...` |

| 1 | ... |
|---|---|
| 2 | `void try_record_audio()` |
| 3 | `int` result = record_audio(buffer, BUFFER_SIZE, RES_AUTO); |
| 4 | `if` (result == -5) |
| 5 | `printf("Could not record audio.\n"));` |
| 6 | `...` |

| 1 | ... |
|---|---|
| 2 | `void try_record_still()` |
| 3 | `int` result = record_frame(buffer, BUFFER_SIZE, RES_AUTO); |
| 4 | `if` (result == -3) |
| 5 | `printf("Could not record still.\n"));` |
| 6 | `...` |

3.4 Future Software Engineering Applications

Future work can apply analogy completion to more varied input/output domains and languages. For example, analogy completion can generate documentation based on existing code, similar to the problem of automated comment generation, which has been addressed by code-clone detection [88].

sentence, or word and estimate how positive or negative it is. Just like with the results of a program analyzer, we can annotate this information on top of the structure, e.g., by marking all symbols representing words which are determined to be highly positive or highly negative by the sentiment analyzer with a unary relation like IsNegativeSentiment. Even though they are not exactly the same word, the fact that they both satisfy the IsNegativeSentiment relation will increase Sifter’s confidence in the analogy.
One might also apply analogy-makers to recover higher-level structure from low-level binaries or compiler intermediate representations. Such information would be useful for decompilation of binary programs [2], in-place binary analysis [81], binary rewriting [85], de-obfuscation of code [65], and identification of code replaceable with highly-optimized libraries [16] or coprocessors [82].

Analogies between existing code with correctness proofs and new code may allow for proof transfer to more quickly prove correctness of the latter. A related technique has been proposed for the Coq theorem prover [62].

More varied information sources can be used for analogy making. For example, the use of information from a profiler may be helpful in a code optimization setting, and compiler error-messages may be useful when using analogies to provide edit suggestions for syntactically-invalid code. This information could be used to rank different proposed analogies or to help find them in the first place.

In a classroom setting, analogy-makers can cluster student assignments, an important problem which is currently addressed via a variety of different techniques [31, 37].

**Sifter** can also detect where a strong analogy *almost holds*, under a small modification its inputs, e.g., in *abc* and *xyf*. If applied to common coding patterns, this might suggest the existence of a bug in the program’s implementation of this pattern. For example, one binary-search implementation might be *almost* analogous to a reference one, except that it computes the midpoint as \((1+h)/2\) instead of \(1+(h-1)/2\), introducing a subtle integer overflow bug that a future version of Sifter might flag as anomalous in the analogy.

### 4 Design of Sifter

In this section, we describe the design of our analogy-making algorithm Sifter and illustrate how it addresses the challenges discussed in Section 3. Its design was influenced by that of Copycat (Section 2.2). However, as we will discuss in Section 6, Copycat’s implementation was specially designed for the letter-analogy domain, whereas we would like to support arbitrary relations and input structures.

At a high level, the behavior of Sifter is formulated as a number of *update rules* operating on a *workspace*. The workspace initially contains a representation of the source code and other inputs which it is supposed to make analogies about. Update rules gradually modify the workspace, both identifying facts, such as when some letter is a successor of another, and making new analogies. Analogies made during this process are explicitly represented within the workspace, as discussed in Section 4.4, and new analogies can build iteratively on existing analogies in the workspace. When a sufficient analogy is found by the system, it can be read off directly from the workspace and returned to the user.

In Section 4.1 we will describe *triplet structures*, a novel data structure used to represent Sifter’s workspace. Triplet structures can represent arbitrary relational facts in a standardized way, making them a particularly flexible tool for representing Sifter’s workspace. In Section 4.2 we will describe how we initialize the triplet structure representing the Sifter workspace for an example analogy problem. In Section 4.3, we introduce a domain-specific language for expressing *update rules* that modify triplet structures, and can be used to infer new facts about the objects in question. Section 4.4 describes how analogies are represented in the workspace, while Section 4.5 describes update rules that can be used to automatically find such analogies.

#### 4.1 Triplet Structures

A *triplet structure* is a novel data structure used to represent the state of Sifter’s workspace. A triplet structure:

1. Represents objects and facts in a standardized form, so that code for operating on the workspace does not have to worry about details like arity of relations.
2. Is able to naturally represent *partial facts*, e.g., we can represent the state “I know letter O is the predecessor of something, but I’m not sure exactly what yet.”
3. Supports efficient lookups and queries, so that operations on the structure can be performed quickly.

**Definition 4.1.** A *triplet structure* is a pair of sets \((S, F)\) where \(F \subseteq S \times S \times S\). We call each member of \(S\) a *node*, each member of \(S \times S \times S\) a *triplet fact*, and \(F\) the set of triplet facts in the structure.

We can encode any finite mathematical structure as a triplet structure with polynomial increase in size. First, for every \(n\)-ary relation \(R\), we add \(n\) nodes to the triplet structure representing slots in the relation. Generally, for an \(n\)-ary relation \(R\) we can always add nodes \(R:1\) through \(R:n\), although we will usually use more descriptive names in our examples. Second, each fact in the original structure gets a *fact node* in the triplet structure, which is a node in \(S\) that *represents the original fact itself* in the triplet structure. For a fact in the original structure of the form \(R(x_1, x_2, \ldots, x_n)\) corresponding to a fact node \(f\), we then add triplet facts of the form \((f, x_i, R:i)\) for every \(i \in \{1, 2, \ldots, n\}\).

Fact nodes in triplet structures can be thought of as C-style *structs*, where each fact \((f, v, k)\) asserts that the field \(k\) in struct \(f\) takes the value \(v\). Alternatively, each fact node \(f\) can be thought of as expressing an interpretation of part of the structure, with a fact \((f, v, k)\) asserting that, in the interpretation \(f, v\) is of type \(k\).

**Example 4.2.** Consider a mathematical structure with objects \(O = \{x, y, z\}\), a single binary relation \(R\), and two relational facts \(R(x, y), R(y, z)\).

To encode this mathematical structure as a triplet structure, we break the binary relation \(R\) into two nodes \(R:1\) and \(R:2\) representing each of its slots. We then create the fact node \(f_1\) for \(R(x, y)\) and the fact node \(f_2\) for \(R(y, z)\). We also
add nodes for each of the original objects in \(O\) to get the set of nodes:
\[
S = \{x, y, z, R:1, R:2, f_1, f_2\}.
\]
Finally, we add triplet facts relating each slot of each fact to arrive at the set of triplet facts in the structure:
\[
F = \{(f_1, x, R:1), (f_1, y, R:2), (f_2, y, R:1), (f_2, z, R:2)\}.
\]

Triplet structures also have an intuitive graph representation. Nodes in the structure correspond to nodes in the graph. For each triplet fact \((f, v, k)\), we add an edge \(v \rightarrow k\) with label \(f\). The graph for the triplet structure considered in this example is the Structure T1 shown below.

**Triplet Structure T1**

Note that, while we have drawn T1 using descriptive names, shapes, and colors, no intrinsic meaning is assigned to any symbol. In the rest of this paper, we will usually only show this visual representation of a triplet structure instead of explicitly listing the nodes and facts. Hence, the reader is encouraged to ensure the connection between the two is well-understood before proceeding.

In addition to directly encoding relational facts, some structures can be more naturally expressed directly as a triplet structure. This is highlighted in the next example.

**Example 4.3.** Consider encoding the scenario “Homer and Marge are the parents of Bart and Lisa.” We may encode this as four facts of the form \(Parent(Homer, Bart), Parent(Homer, Lisa), Parent(Marge, Bart), Parent(Marge, Lisa)\).

With triplet structures, we can express this by saying “Homer, Marge, Bart, and Lisa form a family, where Homer and Marge are the parents, and Bart and Lisa are the children.” This scenario is represented by Structure T2 below.

**Triplet Structure T2**

Another feature of triplet structures is that they can represent partial facts, as demonstrated by the next example.

**Example 4.4.** Suppose in the previous example that we know Abe is the parent of someone, but we are not sure who yet. We represent this uncertainty in Structure T3 below by adding a new fact node \(f_2\), which only states that Abe is a parent, without noting a corresponding child.

**Triplet Structure T3**

If we later learn that Homer is Abe’s child, we can extend \(f_2\) to include this information as shown in Structure T4 below.

**Triplet Structure T4**

4.2 Initializing Workspaces

The Sifter workspace initially contains only symbols representing input objects (such as \(a\) in \(abc\)) and information about their relative position. For example, when comparing the strings \(ab\) and \(ef\), the Sifter workspace is initialized as shown below, where \(x_1\) represents \(a\), \(x_2\) represents \(b\), \(y_1\) represents \(e\), and \(y_2\) represents \(f\).

**Triplet Structure T5**

Notably, we also have nodes like Letter:a representing the Platonic concept of a particular letter; the fact that \(x_1\) is mapped to Letter:a corresponds to asserting the unary IsLetterA(\(x_1\)). We have included nodes for some predicates (specifically Predecessor and Successor representing the slots of the binary LetterSuccessor predicate) that have no incoming or outgoing edges. This indicates that, while Sifter knows about the
concept of predecessor and successor, it has not yet explicitly recognized any letter-successor pairs in the structure. In the next section, we will describe how such facts may be inferred from this initial encoding of the problem via the use of update rules.

4.3 Modifying the Workspace with Update Rules

Sifter proceeds to modify the workspace in two ways: (1) refining the representation of its inputs, e.g., to infer the facts LetterSuccessor(x1, x2) and LetterSuccessor(y1, y2) in the above example, and (2) building an analogy between its inputs by comparing such inferred facts. Both types of modifications are implemented using the same framework of update rules. This section introduces our language for expressing update rules using a simple example rule of the first kind, deferring discussion of the second type of modification to Section 4.4. Note that the language described here for expressing update rules works to define update rules for any triplet structure. However, we focus our examples on their use for expressing inference rules for the Sifter workspace.

Note that, in this section, we will discuss a method of "hard-coding" certain rules to express things like letter-successorship, both because this is how our current implementation operates, as well as to introduce the notion of update rules. Section 4.6 describes more general mechanisms for making such changes without explicitly enumerating all such rules ahead of time.

Recall the initial state of the Sifter workspace for the example of ab and ef, shown above as Structure T5. Consider now the problem of defining a rule that modifies the workspace by identifying when some letter instance is an alphabetical successor of another. For example, we may wish to create a rule that marks instances of the letter ‘a’ and the letter ‘b’ as LetterSuccessor pairs. In first-order logic, we might write the desired rule as IsLetterA(v1) ∧ IsLetterB(v2) \implies LetterSuccessor(v1, v2). We have developed a visual domain specific language (DSL) for expressing such rules operating on the Sifter workspace. Our full DSL is capable of expressing rules containing alternating quantifiers and other pattern-matching features. We will describe here only a simplified subset of the language that suffices for the uses in this paper.

Rules in this DSL look like triplet structures themselves (and in fact can be stored as such), although they are annotated with extra information about which nodes represent variables to search for and how the structure should be modified if such variables are found. For example, Rule R1 below shows a rule which notates a, b letter-successor pairs.

In such rule diagrams, one first looks at the parts not shaded green. In these parts, dashed nodes are variables that should be looked for in the structure, while solid nodes are constants assumed already to exist in the structure. When this pattern is found in the structure, this is called a rule match and the green nodes and facts can be added. In this case, the rule expresses that whenever two nodes v1 and v2 are found such that v1 is the letter ‘a’ and v2 the letter ‘b’, then we can add a new fact node and corresponding triplet facts which express that v2 is an alphabetical successor of v1.

For example, we may apply Rule R1 to Structure T5 by taking the rule assignment with v1 = x1, v2 = x2, v1 = p1, and v2 = p2. This produces a new fact node nf3 which asserts that x1 is a predecessor of the successor x2. Letting s1 be the generated node corresponding to nf3, Rule R1 transforms Structure T5 into Structure T6 below.

Similarly, Rule R2 below identifies e, f pairs as successor pairs.

Applying Rule R2 to Structure T6 marks y1 and y2 as predecessor and successor respectively, producing Structure T7 below.
4.4 Representing Analogies in Triplet Structures

This section discusses how Sifter represents and makes analogies in its triplet-structure workspace. Analogies are represented as abstractions, similar to the abstract letter strings in Section 2. Intuitively, instructed to form an analogy between abc and ef, Sifter forms a shared abstract representation of them both, roughly of the form $a\beta$ with additional information such as $\gamma$ is a successor of $\alpha$. It then adds facts stating that, for example, both the original a and e are instances of this more abstract (?11) object. Two input objects correspond if they are instances of the same abstract node.

Consider the example from Section 4.3, where we are forming an analogy between two letter strings ab and ef. Suppose the current Sifter workspace is represented by Structure T8 below, which is identical to Structure T7 except with a few of the nodes/relations removed for ease of exposition.

In Structure T9, we have added new nodes $\alpha_1$ and $\alpha_2$ to represent the abstract type of which $x_1$, $y_1$, and $x_2$, $y_2$ respectively are instances of. We have also abstracted the fact nodes that correspond to each other into nodes $\alpha n$ and $\alpha s$. These abstract fact nodes each express the same fact about the abstract $\alpha_1$ and $\alpha_2$ as the original, or concrete, fact nodes expressed about, e.g., $x_1$ and $x_2$. Finally, we have added fact nodes $\alpha M_1$ and $\alpha M_2$ that map the concrete nodes in each instance to their abstract counterparts. For bookkeeping reasons in the structure, we label each of these as Abstractions so we can keep track of which nodes in the workspace are abstract vs. provided in the input.

From Structure T9 above, we can extract the analogy that $x_1$ corresponds to $y_1$ because both are instances of the abstract $\alpha_1$ node, and similarly for $x_2$, $y_2$, and $\alpha_2$.

4.5 Rules for Making Analogies in a Triplet Structure

We now turn our attention to designing rules for forming such analogies. All such rules will be of the form discussed in Section 4.3. Each rule application makes a small change to the structure; for example, abstracting two concrete nodes together, or lifting a single concrete fact to the abstraction. These rules create a search space that can be explored using heuristics.

We have found that all of the rules necessary for abstraction-forming can be formed as variations on the following Begin Analogy rule, Rule R3, which starts a new abstraction.
Here, the variable nodes $A$ and $B$ represent the concrete nodes that should correspond to each other in the analogy, like $x_1$ and $y_1$ in the previous example. The variable node $C$ is the field that they both share. For example, in the previous example $C$ might be NextToLeft, because both $x_1$ and $y_1$ are mapped to NextToLeft by fact nodes $n_1$ and $n_2$, which in turn map to $M_A$ and $M_B$, respectively, in the rule above.

Applying Rule R3 to Structure T9 may produce the start of an analogy shown below in Structure T10. For clarity, we have left out the facts between concrete nodes.

By shading different subsets of the nodes green, we can modify Rule R3 into a variety of rules for extending analogies. For example, Rule R4 below "follows" a fact node from an existing analogy to map two new concrete nodes to each other.

Applying Rule R4 to our running structure with $A = x_2$, $B = y_2$, and $C = \text{NextToRight}$ would extend the analogy to include $x_2$ and $y_2$ by "following" the NextToRight relation, producing Structure T11 below.

Similarly, by shading just the $aM_{AB}$ node, we get Rule R5 that adds a new fact node to the abstraction.

Applying Rule R5 to the previous abstraction with $A = x_1$, $B = y_1$, $\alpha AB = \alpha_1$, $C = \text{Predecessor}$, $M_A = s_1$, and $M_B = s_2$ allows us to associate $s_1$ and $s_2$ with each other, producing Structure T12 as shown below.
4.6 Higher-Order Analogies and Slips

We described in Section 4.3 that rules could be used to infer new facts, such as $\text{LetterSuccessor}(x_1, x_2)$. Such facts could later be used in analogies, e.g., to compare $ab$ and $ef$ as “two-letter strings where the letters satisfy the LetterSuccessor relation”. To do this, we had to first explicitly add the facts $\text{LetterSuccessor}(x_1, x_2)$ and $\text{LetterSuccessor}(y_1, y_2)$. In general, this approach requires us to explicitly enumerate rules for all such relations used in our analogies. This section considers a more general approach based on forming analogies between types in the structure.

At first glance, it is tempting to resolve the issue using a general transitivity rule such that, for example, if $x_1$ is an instance of $T_1$, $x_2$ is an instance of $T_2$, and there is some fact $R(T_1, T_2)$, then we can add $R(x_1, x_2)$ as well. For example, if $\text{LetterSuccessor}(\text{Letter} : a, \text{Letter} : b)$ and $x_1$ was an instance of $\text{Letter} : a$, $x_2$ an instance of $\text{Letter} : b$, then the rule would infer $\text{LetterSuccessor}(x_1, x_2)$ as desired.

However, facts about types may not be valid or well-defined when applied to instances of those types. For example, when forming an analogy involving both numerical value and color, we may have two nodes be instances of opposite numbers, e.g., $-1$ and $1$, or opposite colors, e.g., black and white. If we were to directly use transitivity to say that the two nodes were simply “opposites,” we would lose important information because we would not know whether they were opposite numbers or colors. Similarly, consider forming an analogy between the pairs $abc \rightarrow cba$ and $efg \rightarrow gfe$. Fundamentally, what we want to express is that the letters in the first string satisfy either $\text{LetterSuccessor}$ or $\text{LetterPredecessor}$, and that those in the second string satisfy the opposite.

To express such scenarios naturally, we need a way to include the types in the analogy, i.e., make a type slip. In the mapping rules shown so far, we require the both concrete nodes $A$ and $B$ to be of the same type $C$. However, we can define new mapping rules, using the template of Rule R7, that allow the type itself to be abstracted and become part of the analogy. In the example discussed, we could have $\text{LetterSuccessor}$ be $C_1$ and $\text{LetterPredecessor}$ be $C_2$. 
Although allowing for creative analogies, such an approach significantly increases the search space. To control this, one can make compound analogies, using type slips only for small sub-analogies with smaller search spaces. Then those analogies are used to define types with which to build up larger ones. For example, we could use a type slip to learn the abstract type of "pairs of nodes which are instances of types that have Successor relation," i.e., effectively re-learn the LetterSuccessor relation on its own. Analogy-making rules could then be used to note that both $x_1$, $x_2$ and $y_1, y_2$ form an instance of this abstract type, and then the abstract type can be used exactly like Predecessor and Successor in future analogies.

5 Efficient Software Analogies with Sifter

This section discusses practical considerations with the application of Sifter to make analogies of the form shown in Section 3. We focus on three particular factors, (i) the representation of source code as a triplet structure, (ii) the use of other sources of reasoning and information, and (iii) heuristics for finding analogies. In each section, we begin with a description of our current solution, then discuss our vision of what a future implementation may be able to accomplish.

5.1 Representing Source Code as Triplet Structures

Currently, given a source file we perform a lightweight lexical analysis before encoding it in the structure. If more information about the meaning of some of the resulting lexemes is known, we can include that as well. For example, given a source file consisting only of the statement `name = user . name`, we might encode it as shown in Structure T12.

For brevity, 11 fact nodes are not explicitly shown. However, their existence is implied by the colors and labels on the edges. We first create a node in the structure representing the file. For each lexeme in the file we add a corresponding node. Each lexeme node is marked as a member of the corresponding file, and their relative positions are specified using `NextToLeft` and `NextToRight`. There are four nodes representing Platonic strings (or 'tokens'), which play the same role as the `Letter:a` nodes in Section 4.3 or a unary `IsLetterA(x)` predicate. In this example, we assume additional information about the language, namely that `user . name` represents an access of the `name` field of the `user` object.

Notably, such a lexical analysis can usually be developed quite quickly even for new programming languages. At its...
simplest, it can be implemented as just splitting the source file based on whitespace and special characters such as *.

This allows for Sifter to be applicable to nascent DSLs and other languages where a full compiler and AST generator has not yet been developed, or to work with syntactically-invalid programs. As the language tooling grows in maturity or parts of the programs become syntactically valid, more detailed information can be produced from the lexing pass and included in the structure, such as the object-field access noted in the above example.

**Future Work: Full ASTs** While the progressive-lexing style of encoding strikes a nice balance between flexibility and richness, if a full AST is readily available for the code in question, then this can be used to produce a richer encoding of the structure. Structure T13 shows how an AST for the name=user. name example might be encoded as a triplet structure.

![Triplet Structure T13](image)

**Future Work: Multiple Granularities** One particularly exciting area of future work for our encoding is to allow the granularity of the encoding to change dynamically, as the analogy process is proceeding. In this model, the workspace would initially begin with only a listing of the names of files and folders in the root directory of the project(s). As analogy-making proceeds, the contents of files may be added to the structure either randomly or according to activity from the analogy-making process itself. For example, if two files are named the same, they may be mapped together indicating their importance to the analogy and hinting to the system that the file contents might be important as well. If more semantic information about the programming languages is known, this type of multi-granularity encoding can be used at that level as well. For example, a file could be loaded first as just a list of functions contained in it. If two functions seem similar based on their signatures, then we expand them and include the full associated code in the workspace.

Our current implementation supports such real-time modifications to the structure, like adding a new file’s contents halfway during an analogy run. However, the heuristics for knowing when to do such are not yet developed, so we just add the full contents of the files to it at the start (limiting us to small-ish projects).

**5.2 Use of Other Engines**

Many other reasoning engines for both natural language and software source-code exist, including logic-based techniques (such as Cyc [42]), abstract interpretation [14], and statistical techniques (such as deep learning [27]). We designed Sifter with the specific goal of easily integrating the knowledge stored in such tools with the analogy-making process. In particular, while we focused in Section 4.3 on the usage of update rules to make inferences about relations such as LetterSuccessor, there is no requirement that modifications to the structure come from such a update rule. Instead, other reasoning engines can provide their own insights into the problem at hand, which can then be translated into triplet facts and added to the structure. Such added facts are used in analogies just like any other facts.

For example, a statistical model might be used to identify when words used are synonyms, which can be encoded into the workspace, e.g., using a Synonym predicate or by stating that both words are instances of some common semantic notion. Similarly, a logical inference engine like Cyc [42] might be used to understand comments in, e.g., function docstrings to identify the semantic meaning behind different functions, or infer the effects of applying multiple different functions in sequence. This information can be encoded back into the triplet structure and used to make analogies.

**Future Work: A Unified Workspace** We envision that the triplet structure workspace of Sifter can serve as a shared workspace among a host of reasoning engines. The core analogy-making rules, which operate structurally, and are in some sense oblivious to the semantics of the relations, can act as glue that can help synthesize inferences across distinct reasoning engines. Reasoning engines can operate independently, inferring new facts and adding them to the structure. Furthermore, they may be able to use the facts inferred by other engines or even predicted to be true via analogy to further their own reasoning, resulting in a virtuous cycle of cooperation between different engines.

**Future Work: Probabilistic Triplet Structures** To better interface with statistical models, it may be desirable to associate with each triplet fact a corresponding real-valued probability representing Sifter’s confidence in that inferred fact. As future inferences are made, their confidence values can be computed as a function of the confidence in that specific step as well as the confidence in the facts it relies on to make that inference. However, as argued by the Cyc authors [42], one should be careful in treating such numbers as a measure of truthfulness of a claim, and instead only as a representation of one’s epistemological uncertainty about immediate observations of the environment.
5.3 Heuristics for and Identification of Strong Software Analogies

To guide the search process, we need a notion of the strength of an analogy. One initial approach to this is to define a stronger analogy as one with more shared facts. This idea can be improved by weighting different types of relations with an importance. For a somewhat extreme example, we may prefer to map two functions together that share a relation of “called by analogous methods” rather than simply “share the same first letter.” This approach is exemplified by the notion of a Slipnet in the Copycat architecture, which assigns numerical, a priori importances to each type of relation.

For scenarios where the goal of the analogy is to generate some completion (as in Section 3.2 and 3.3), we have found that an even stronger heuristic measure of analogy depth is to check if a full completion to the original problem can be made from it. In our experience, when we had bugs with our search process, we found that the completions produced in Figure 2 and 4 would either (i) contain very few nodes, or (ii) contain many nodes that the system thought would be there, but was not able to actually infer (consistently) what tokens they should be. This can be used to indicate when an analogy may fit the two examples very well, but does not generalize to the prompt.

Future Work: Cognitive Models In the long term, we are excited about the possibility of having multiple workers that operate concurrently, either working on separate attempts at making such analogies, finding inconsistencies in analogies made by others, or working together to produce a strong analogy. Such a system may take inspiration from psychology-inspired architectures and theories, like LIDA [22] and Global Workspace Theory [3]. Such a system could be supplemented via the use of something akin to abduction, where rules can request the help of other rules. For instance, an abstraction rule expressing that it would be able to abstract two things together if only one of them were also a letter successor would encourage rules to search for letter successor facts relating to that node. This abductive inference is similar to the execution of the Slipnet and Coderack in the original Copycat algorithm.

Future Work: Meta-Reasoning Sifter may be extended to support meta-reasoning similar to that of Metacat [49], where the system learns to recognize common ‘snags’ that it can store and refer back to when it encounters a new problem that is challenging in the same way. It may recognize such “challenging in the same way” instances via a sort of meta-Sitter, forming analogies between solver states. In such a way, it would be able to effectively introspect on its own solving process via a (copy of) the solver itself. Such a system may be aided by the fact that our Sitter update rules can be expressed within triplet structures themselves.

6 Related Work

Analogy making Analogies, and the more general class of metaphors [40, 41], have been studied extensively in cognitive science. The primary inspiration for this paper was the Copycat algorithm of Melanie Mitchell and Douglas Hofstadter [34, 35], which we generalized into the Sifter analogy-making algorithm presented here. Mitchell’s original source code [12] is written in a now-defunct dialect of Common Lisp for which we could not obtain an interpreter. Thankfully, there are a number of more-modern ports [11, 13] which we were able to reference and run. We originally intended to adapt these implementations for use on program source code, but quickly found that the Copycat algorithm is highly specific for the letter string domain. Adding support even for upper-case letters, for example, turned out to be a significant project, touching almost every file in the implementation. This is because Copycat implements relations like LetterPredecessor by special-case checks and data structures throughout the code, not as the sort of arbitrary relations that are more familiar in systems based on first-order logic. These issues motivated the construction of our Sifter analogy-making algorithm.

Beyond Copycat, there are a number of other analogy-making algorithms explored in the cognitive science and philosophy literature, such as SME [20], ACME [36], Winston’s Analogy-Maker [87], and the Geometric Analogy-Maker [19]. Below we will discuss SME, but ACME and Winston’s algorithm have a similar operation. The Geometric Analogy-Maker is interesting and unique, incorporating some amount of grouping and representational manipulation similar to that of Copycat, although it is specific to geometric analogy problems.

The Structure Mapping Engine (SME) [20] is an analogy-making algorithm that gained notoriety for, among other things, “discovering” the Rutherford model of the atom by analogy to a solar system [24]. Its basic operation is similar to that of a sub-graph isomorphism algorithm, in that it looks for an injective mapping between the objects and predicates in one structure into those of another that retains the facts. The SME algorithm has been criticized by some [34] for its reliance on hand-written input representations, which circumvents the hardest part of analogy-making. For example, when forming an analogy between the strings aaabbc and abbbcc, it might be natural for a human to group the three aaas and associate them either with the single a or the similar group-of-three ccc in the second. However, SME has no conception of modifying the structure, or its representation of the structure, in such a way. The user would have to explicitly group letters before providing it to SME, at which point SME would just look for relations between groups.

The Sifter workspace represents a its workspace using structures and relations. Similarly, TVLA [43, 72, 73] represents possible program states using a variant of first-order
logic. In TVLA, such structures are abstracted into three-valued structures, somewhat similar to how we abstract concrete instances in the workspace to form analogies.

**Comparative program understanding** The problem of comparative program understanding is related to the problem of code detection [23, 38, 39, 48, 71] with recent approaches using deep learning [86]. CP-Miner identifies bugs related to copy-pasted code [44]. The func2vec technique computes function embeddings to learn function synonyms, which are functions are play a similar role in the source code [15]. Such function synonyms are used to identify error-handling bugs in the Linux kernel. The code2vec technique computes an embedding of source code using the AST [1], which can be used to infer names of functions. These techniques represent a research thread that uses “Big Code” [84]. In contrast, Sifter uses relatively limited amount of source code to make analogies; however, it can make use of models of source code learned via deep learning and other techniques.

**Program transformation-learning** Recent approaches, such as GetAFix [4], have explored the use of antiunification of program ASTs to learn program fixes. Such antiunification can be seen as a restricted special case of the analogy-as-abstraction process used by Sifter (see Section 4.4). Existing antiunification-based approaches, however, are limited to tree structures (such as ASTs), and can not make use of additional semantic information. For example, GetAFix would not have been able to accurately learn the transformation in Section 3.2, which relied on semantic properties of the code, or the one in Section 3.3, which relied on referencing the documentation.

The program transformation-learning problem is related to Programming by Example [28–30, 51, 66, 77–80, 89]. Such techniques typically restrict the program transformation to a limited domain-specific language. Repenning et al. [68] describe how end-users of a programming-by-example system might use analogies to express the desired behavior by comparison to that of an existing program. Perrone et al. [61] propose that implementing code reuse via concrete analogies can be more natural than the use of standard object-oriented programming paradigms and help novice programmers avoid copy-and-pasting code. Recent approaches have explored using natural language and examples as input [67] and using deep learning techniques [83].

**API Migration** Many approaches for API migration that use statistical and machine learning techniques have been proposed [55–59, 63].

**Cognitive Science in SE** There are numerous works which have highlighted the promise of models from cognitive science in software engineering. Call by Meaning [74] describes a system in which program components (e.g., functions) can be addressed by their semantic meaning, not just their syntactic name. A programmer may describe an existing function using a high-level, semantic description language and the Cyc [42] cognitive model will be used to infer which (composition of) function(s) best matches that description. The Semprola semiotic programming language [76] allows programmers to directly use signs instead of the now-dominant focus on textual code symbols. Both Call by Meaning and Semprola are ambitious and exciting projects, requiring a fundamental re-thinking of how and in what languages we write code. While we envision that Sifter can benefit such approaches in the future, we are excited that, as described in Section 3, Sifter can wield these cognitive models to more immediately benefit software engineers using the existing programming languages and environments of today.

## 7 Conclusion

In this paper, we discussed analogy-making, a fundamental human ability that involves identifying underlying similarities between two objects. We first described analogy-making through examples in a restricted letter-string domain. We then showed how analogy-making can be used to address a variety of software engineering tasks, namely comparative program understanding, program optimization, and API migration. Finally, we described Sifter, our proposed algorithm for analogy-making, which is suitable for making analogies about programs. Sifter relies on a novel triplet-structure representation for its workspace, allowing it to form analogies over arbitrary inputs, such as source code, program analyzer outputs, and documentation. By reducing a variety of problems to analogy-making, improvements to the core analogy-making primitive can pay large dividends across a variety of applications. Software engineering represents a difficult challenge for analogy-making, as it involves a unique balance of unambiguous syntax and semantics of the program, as well as ambiguous information about programmer intent. We hope that this paper serves as a first step towards cementing analogy-making as a core primitive in the software engineering toolbox.

## Acknowledgments

We thank the anonymous reviewers and Cindy Rubio González for comments that significantly improved this paper.

## References

[1] Uri Alon, Meital Zilberstein, Omer Levy, and Eran Yahav. 2019. code2vec: learning distributed representations of code. Proc. ACM Program. Lang. 3, POPL (2019), 40:1–40:29.

[2] Dennis Andriesse, Xi Chen, Victor Van Der Veen, Asia Slowinska, and Herbert Bos. 2016. An in-depth analysis of disassembly on full-scale x86/x64 binaries. In 25th {USENIX} Security Symposium ({USENIX} Security 16), 583–600.

[3] Bernard J Baars. 1993. A cognitive theory of consciousness. Cambridge University Press.

[4] Johannes Bader, Andrew Scott, Michael Pradel, and Satish Chandra. 2019. Getafix: learning to fix bugs automatically. Proceedings of the ACM on Programming Languages 3, OOPSLA (2019), 1–27.

[5] Paul Bartha. 2019. Analogy and Analogical Reasoning. In The Stanford Encyclopedia of Philosophy (spring 2019 ed.), Edward N. Zalta (Ed.).
Onward! '20. November 15–20, 2020, Chicago, IL
Sotoudeh and Thakur

Metaphysics Research Lab, Stanford University.

[6] bash 2020. fish - the friendly interactive shell. https://github.com/fish-shell/fish-shell. Accessed May, 2020.

[7] bash 2020. GNU Bash. https://ftp.gnu.org/gnu/bash/. Accessed May, 2020.

[8] Fraser Brown, Andreas Nötzli, and Dawson Engler. 2016. How to build static checking systems using orders of magnitude less code. In Proceedings of the Twenty-First International Conference on Architectural Support for Programming Languages and Operating Systems. 145–157.

[9] John Clement. 1993. Using bridging analogies and anchoring intuitions to deal with students’ preconceptions in physics. Journal of research in science teaching 30, 10 (1993), 1241–1257.

[10] CNN. 2020. The ‘healing hearts’ of these pulsating stars create music to astronomers’ ears. https://www.cnn.com/2020/05/15/world/pulsating-stars-delta-scuti-scn-trnd/index.html. Accessed May, 2020.

[11] copycat 2020. Modern port of Melanie Mitchell’s and Douglas Hofstadter’s Copycat. https://github.com/fargonauts/copycat. Accessed May, 2020.

[12] copycat 2020. Original Copycat Source Code. http://web.cecs.pdx.edu/~mm/how-to-get-copycat.html. Accessed May, 2020.

[13] copycat 2020. A translation of Melanie Mitchell’s original Copycat project from Lisp to Python. https://github.com/ajhager/copycat. Accessed May, 2020.

[14] Patrick Cousot and Radhia Cousot. 1977. Abstract Interpretation: A Unified Lattice Model for Static Analysis of Programs by Construction or Approximation of Fixpoints. In POPL. ACM, 238–252.

[15] Daniel DeFrees, Aditya V. Thakur, and Cindy Rubio-González. 2018. Path-based function embedding and its application to error-handling specification mining. In ESEC/SIGSOFT FSE. ACM, 423–433.

[16] Edoardo Di Napoli, Diego Fabregat-Traver, Gregorio Quintana-Ortí, and Paolo Bientinesi. 2014. Towards an efficient use of the BLAS library for multilinear tensor contractions. Appl. Math. Comput. 235 (2014), 454–468.

[17] Sarah A Douglas and Thomas P Moran. 1983. Learning text editor semantics by analogy. In Proceedings of the SIGCHI conference on Human Factors in Computing Systems. 207–211.

[18] Enda Dunican. 2002. Making the Analogy: Alternative Delivery Techniques for First Year Programming Courses. In Proceedings of the 14th Annual Workshop of the Psychology of Programming Interest Group. PPG 2002, London, UK, June 18-21, 2002. Psychology of Programming Interest Group, 8.

[19] Thomas G Evans. 1964. A heuristic program to solve geometric-analogy problems. In Proceedings of the April 21-23, 1964, spring joint computer conference. 327–338.

[20] Brian Falkenhainer, Kenneth D Forbus, and Dedre Gentner. 1989. The structure-mapping engine: Algorithm and examples. Artificial intelligence 41, 1 (1989), 1–63.

[21] Michal Forisek and Monika Steinová. 2012. Metaphors and analogies for teaching algorithms. In Proceedings of the 43rd ACM technical symposium on Computer Science Education. 15–20.

[22] Stan Franklin, Tamas Madi, Sidney Difnello, and Javier Snaider. 2013. LIDA: A systems-level architecture for cognition, emotion, and learning. IEEE Transactions on Autonomous Mental Development 6, 1 (2013), 19–41.

[23] Mark Gabel, Lingxiao Jiang, and Zhendong Su. 2008. Scalable detection of semantic clones. In 30th International Conference on Software Engineering (ICSE 2008), Leipzig, Germany, May 10-18, 2008. 321–330.

[24] Dedre Gentner. 1983. Structure-mapping: A theoretical framework for analogy. Cognitive science 7, 2 (1983), 155–170.

[25] Dedre Gentner, Jeffrey Loewenstein, and Leigh Thompson. 2003. Learning and transfer: A general role for analogical encoding. Journal of Educational Psychology 95, 2 (2003), 393.

[26] Nasser Giacaman. 2012. Teaching by example: using analogies and live coding demonstrations to teach parallel computing concepts to undergraduate students. In 2012 IEEE 26th International Parallel and Distributed Processing Symposium Workshops & PhD Forum. IEEE, 1295–1298.

[27] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. 2016. Deep learning. MIT press.

[28] Sumit Gulwani. 2011. Automating string processing in spreadsheets using input-output examples. In Proceedings of the 38th ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages, POPL 2011, Austin, TX, USA, January 26-28, 2011. 317–330.

[29] Rahul Gupta, Aditya Kanade, and Shirish Shevade. 2019. Deep reinforcement learning for syntactic error repair in student programs. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33. 930–937.

[30] Onward! '20. November 15–20, 2020, Chicago, IL Sotoudeh and Thakur

[31] Tal Lev-Ami and Shmuel Sagiv. 2000. TVLA: A System for Implementing Deep Approximation of Fixpoints. In Proceedings of the 14th Annual Workshop of the Psychology of Programming Interest Group. PPG 2002, London, UK, June 18-21, 2002. Psychology of Programming Interest Group, 8.

[32] Douglas Hofstadter. 1995. A Review of Mental Leaps: Analogy in Creative Thought. AI Magazine 16, 3 (1995), 75–80.

[33] Douglas Hofstadter. 1995. fluid concepts and creative analogies: Computer models of the fundamental mechanisms of thought. Basic books.

[34] Douglas Hofstadter and Melanie Mitchell. 1994. The Copycat project: A model of mental fluidity and analogy-making. (1994).

[35] Keith J Holyoak and Paul Thagard. 1989. Analogical mapping by constraint satisfaction. Cognitive science 13, 3 (1989), 295–355.

[36] Shalini Kaleeswaran, Anirudh Santhiar, Aditya Kanade, and Sumit Gulwani. 2016. Semi-Supervised Verified Feedback Generation. In Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering (Seattle, WA, USA) (FSE 2016). Association for Computing Machinery, New York, NY, USA, 739f/739–750. https://doi.org/10.1145/2950290.2950363

[37] Yoshihiro Kamiya, Shinji Kusumoto, and Katsuro Inoue. 2002. CCFinder: a multilingual token-based code clone detection system for large scale source code. IEEE Transactions on Software Engineering 28, 7 (2002), 654–670.

[38] Raghavan Konomdoor and Susan Horwitz. 2001. Using Slicing to Identify Duplication in Source Code. In Static Analysis, 8th International Symposium, SAS 2001, Paris, France, July 16-18, 2001, Proceedings. 40–56.

[39] George Lakoff and Mark Johnson. 2008. Metaphors we live by. University of Chicago press.

[40] George Lakoff and Rafael Núñez. 2000. Where mathematics comes from. Vol. 6. New York: Basic Books.

[41] Douglas B Lenat. 1995. CYC: A large-scale investment in knowledge infrastructure. Commun. ACM 38, 11 (1995), 33–38.

[42] Tal Lev-Ami and Shmuel Sagiv. 2000. TVLA: A System for Implementing Static Analyses. In Static Analysis, 7th International Symposium, SAS 2000, Santa Barbara, CA, USA, June 29 - July 1, 2000, Proceedings (Lecture Notes in Computer Science, Vol. 1824), Jens Pelzgen (Ed.). Springer, 280–301. https://doi.org/10.1007/978-3-540-45099-3_15

[43] Zhou Min, Li, Shun Lu, Sunuda Myagmar, and Yuanuyuan Zhou. 2006. CP-Miner: Finding copy-paste and related bugs in large-scale software code. IEEE Transactions on software Engineering 32, 3 (2006), 176–192.

[44] Sifei Luan, Di Yang, Celeste Barnaby, Koushik Sen, and Satish Chandra. 2019. Aroma: Code recommendation via structural code search. Proceedings of the ACM on Programming Languages 3, OOPSLA (2019),
Analogy-Making as a Core Primitive in the Software Engineering Toolbox Onward! ’20, November 15–20, 2020, Chicago, IL

1–28.

[Katherine N Macfarlane and Barbee T Mynatt. 1988. A study of an advance organizer as a technique for teaching computer programming concepts. ACM SIGCSE Bulletin 20, 1 (1988), 240–243.

[Solomon Maima, Anders Miltner, Kathleen Fisher, Benjamin C Pierce, David Walker, and Steve Zdancewic. 2018. Synthesizing quotient lenses. Proceedings of the ACM on Programming Languages 2, ICFP (2018), 1–29.

[Andrian Marcus and Jonathan I Maletic. 2001. Identification of high-level concept clones in source code. In Proceedings 16th Annual International Conference on Automated Software Engineering (ASE 2001). IEEE, 107–114.

[James B Marshall. 2000. Metacat: A self-watching cognitive architecture for analogy-making and high-level perception. (2000).

[Anders Miltner, Kathleen Fisher, Benjamin C Pierce, David Walker, and Steve Zdancewic. 2017. Synthesizing bijection lenses. Proceedings of the ACM on Programming Languages 2, POPL (2017), 1–30.

[Anders Miltner, Sumit Gulwani, Vu Le, Alan Leung, Arjun Radhakrishna, Gustavo Soares, Ashish Tiwari, and Abhishek Udupa. 2019. On the Fly Synthesis of Edit Suggestions. Proc. ACM Program. Lang. 3, OOPSLA, Article 143 (Oct. 2019), 29 pages. https://doi.org/10.1145/3360569.

[Martin Lee Minsky. [n.d.]. Logical vs. Analogical; or Symbolic vs. Connectionist; or Neat vs. Scruffy. ([n. d.]).

[Matthew W Moskewicz, Conor F Madigan, Ying Zhao, Lintao Zhang, and Marvin Lee Minsky. [n.d.]. Logical vs. Analogical; or Symbolic vs. Connectionist; or Neat vs. Scruffy. ([n. d.]).

[Tien N. Nguyen. 2016. Code migration with statistical machine translations. In Proceedings of the 5th International Workshop on Software Mining, SoftwareMining@ASE 2016, Singapore, Singapore, September 3, 2016, 2.

[Emma Nilsson-Nyman, Torbjörn Ekman, and Görel Hedin. 2008. Practical scope recovery using bridge parsing. In International Conference on Software Language Engineering, Springer, 95–113.

[Corrina Perrone and Alexander Repenning. 1998. Graphical rewrite rule analogies: avoiding the inherit or copy and paste reuse dilemma. In Proceedings. 1998 IEEE Symposium on Visual Languages. IEEE, 40–46.

[Frank Pfening. 1991. Unification and Anti-Unification in the Calculus of Constructions. In In Sixth Annual IEEE Symposium on Logic in Computer Science. 74–85.

[Hung Dang Phan, Anh Tuan Nguyen, Trong Duc Nguyen, and Tien N. Nguyen. 2017. Statistical migration of API usages. In Proceedings of the 39th International Conference on Software Engineering, ICSE 2017, Buenos Aires, Argentina, May 20-28, 2017 - Companion Volume. 47–50.

[Noah S Policofsky and Noah D Finkelstein. 2006. Use of analogy in learning physics: The role of representations. Physical Review Special Topics-Physics Education Research 2, 2 (2006), 020101.

[Veselin Raychev, Martin Vechev, and Andreas Krause. 2015. Predicting program properties from “big code”. ACM SIGPLAN Notices 50, 1 (2015), 111–124.

[Mohammad Raza and Sumit Gulwani. 2018. Disjunctive Program Synthesis: A Robust Approach to Programming by Example. In Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2–7, 2018. 1403–1412.

[Mohammad Raza, Sumit Gulwani, and Natasia Milic-Frayling. 2015. Compositional Program Synthesis from Natural Language and Examples. In Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, IJCAI 2015, Buenos Aires, Argentina, July 25-31, 2015. 792–800.

[Alexander Repenning and Corrinia Perrone. 2000. Programming by example: programming by analogous examples. Commun. ACM 43, 3 (2000), 90–97.

[Lindsey E Richland, Keith J Holyoak, and James W Stigler. 2004. Analogy use in eighth-grade mathematics classrooms. Cognition and instruction 22, 1 (2004), 37–60.

[Lindsey E Richland, Osnat Zur, and Keith J Holyoak. 2007. Cognitive supports for analogies in the mathematics classroom. Science 316, 5828 (2007), 1128–1129.

[Chanchal K Roy, James R Cordy, and Rainer Koschke. 2009. Comparison and evaluation of code clone detection techniques and tools: A qualitative approach. Science of computer programming 74, 7 (2009), 470–495.

[Shmuel Sagiv, Thomas W. Reps, and Reinhard Wilhelm. 1999. Parametric Shape Analysis via 3-Valued Logic. In POPL ’99, Proceedings of the 26th ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages, San Antonio, TX, USA, January 20-22, 1999, Andrew W. Appel and Alex Aiken (Eds.). ACM, 105–118. https://doi.org/10.1145/292540.292552.

[Shmuel Sagiv, Thomas W. Reps, and Reinhard Wilhelm. 2002. Parametric shape analysis via 3-valued logic. ACM Trans. Program. Lang. Syst. 24, 3 (2002), 217–298. https://doi.org/10.1145/514188.514190.

[Hesam Samimi, Chris Deaton, Yoshiki Ohshima, Alessandro Warth, and Todd Millstein. 2014. Call by meaning. In Proceedings of the 2014 ACM International Symposium on New Ideas, New Paradigms, and Reflections on Programming & Software. 11–28.

[Yam San Chee. 1993. Applying Gentner’s theory of analogy to the teaching of computer programming. International journal of man-machine studies 38, 3 (1993), 347–368.

[Oli Sharpe. 2018. Semprola: a semiotic programming language. In Conference Companion of the 2nd International Conference on Art, Science, and Engineering of Programming, 202–213.

[Rishabh Singh. 2016. BlinkFill: Semi-supervised Programming By Example for Syntactic String Transformations. Proc. VLDB Endow. 9, 10 (2016), 816–827.

[Rishabh Singh and Sumit Gulwani. 2012. Learning Semantic String Transformations from Examples. Proc. VLDB Endow. 5, 8 (2012), 740–751.

[Rishabh Singh and Sumit Gulwani. 2016. Transforming spreadsheet data types using examples. In Proceedings of the 43rd Annual ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages, POPL 2016, St. Petersburg, FL, USA, January 20 - 22, 2016. 343–356.

[David Canfield Smith. 1975. Pygmalion: a creative programming environment. Technical Report. STANFORD-univ CA DEPT OF COMPUTER SCIENCE.
[81] Dawn Song, David Brumley, Heng Yin, Juan Caballero, Ivan Jager, Min Gyung Kang, Zhenkai Liang, James Newsome, Pongsin Poosankam, and Prateek Saxena. 2008. BitBlaze: A new approach to computer security via binary analysis. In *International Conference on Information Systems Security*. Springer, 1–25.

[82] Matthew Sotoudeh, Anand Venkat, Michael Anderson, Evangelos Georganas, Alexander Heinecke, and Jason Knight. 2019. ISA mapper: a compute and hardware agnostic deep learning compiler. In *Proceedings of the 16th ACM International Conference on Computing Frontiers*. 164–173.

[83] Marko Vasic, Aditya Kanade, Petros Maniatis, David Bieber, and Rishabh Singh. 2019. Neural Program Repair by Jointly Learning to Localize and Repair. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*.

[84] Martin T. Vechev and Eran Yahav. 2016. Programming with "Big Code". *Found. Trends Program. Lang.* 3, 4 (2016), 231–284. https://doi.org/10.1561/2500000028

[85] Matthias Wenzl, Georg Merzdovnik, Johanna Ullrich, and Edgar Weippl. 2019. From hack to elaborate technique??a survey on binary rewriting. *ACM Computing Surveys (CSUR)* 52, 3 (2019), 1–37.

[86] Martin White, Michele Tufano, Christopher Vendome, and Denys Poshvyvanyk. 2016. Deep learning code fragments for code clone detection. In *2016 31st IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 87–98.

[87] Patrick H Winston. 1980. Learning and reasoning by analogy. *Commun. ACM* 23, 12 (1980), 689–703.

[88] Edmund Wong, Taiyue Liu, and Lin Tan. 2015. Clocom: Mining existing source code for automatic comment generation. In *2015 IEEE 22nd International Conference on Software Analysis, Evolution, and Reengineering (SANER)*. IEEE, 380–389.

[89] Moshe M. Zloof. 1977. Query-by-example: A data base language. *IBM systems Journal* 16, 4 (1977), 324–343.
A Efficient Implementation of Sifter

A.1 Efficient Rule Matching in Triplet Structures

Most operations on the workspace need to quickly look for patterns in the triplet structure. Therefore, it is useful to represent the triplet structure in such a way that many lookups are fast. Thankfully, because of the uniformity of the triplet representation, we can do this. Internally, we represent triplet structures by a hashmap, which takes triplets with holes to a list of triplets. In the example from Section 4.1, we would associate with the key \((?, ?, \text{NextToLeft})\) the set of facts \(((f_1, a, \text{NextToLeft}), (f_2, b, \text{NextToLeft}))\). When adding a new fact to the structure, we add it to the \(2^3 = 8\) hashmaps formed by replacing some subset of its indices with a hole. This is a relatively manageable constant-factor overhead.

With this representation, we can reduce looking for a node satisfying some pattern to simply intersecting sets. For example, if we wanted to find a node \(v\) which is “in the middle of a string,” i.e. to the left of some node and to the right of another, we would use the constraints \((?, v, \text{NextToLeft})\) and \((?, v, \text{NextToRight})\). Since these are existential constraints in only a single variable, we can solve them by intersecting

\[
\{ t_2 \mid (t_1, t_2, t_3) \in H[?(?, \text{NextToLeft})]\} \cap \{ t_2 \mid (t_1, t_2, t_3) \in H[?(?, \text{NextToRight})]\}.
\]

Solving more complex constraints (e.g., finding multiple nodes which together satisfy some constraints) is still an NP-hard constraint satisfaction problem in triplet structures, but such efficient single-variable existential lookups helps form the core of our solver for more complex constraint problems.

A.2 Differential, Symmetric, and Local Rule Matching

In addition to efficiently storing the triplet structures, Sifter uses the following three other optimizations to speed up rule pattern matching.

First, Sifter makes use of differential matching. The fundamental observation is that, at least for the first existential layer of a rule, adding facts to the structure can only ever add more possible rule assignments, so every such new rule assignment must use one of the newly-added facts. Hence, Sifter can keep track of which facts have been added to the structure since it last looked for rule assignments, and only consider assignments which use those new facts. A similar technique works for filtering out old assignments that use removed facts.

Second, we note that many rules have symmetries, where a valid variable assignment can be permuted to form a new valid variable assignment. Under certain conditions, Sifter can take advantage of these symmetries to only search for assignments to half of the variables, then consider all permutations to get the rest of the variables.

Finally, heuristics can be used to localize the rules. For example, Sifter can only look for rules that match to symbols nearby a symbol modified on the last update rule application (this is similar to the operation of the Slipnet in Copycat).

A.3 Commutative Node Names

Many interesting search heuristics require reasoning across different branches of the search tree. For example, phase saving is used by SAT solvers such as Chaff [53], where after backtracking and choosing another assignment to variable \(v_i\), the solver will attempt to perform the same assignments to \(v_j\) for \(j > i\) as were made before the backtrack.

To apply analogous heuristics to the type of search over update rule applications in Sifter, we need to be particularly careful about how we reference nodes in the structure. This is because rules can operate on nodes created by other rules. If we give newly-created nodes random names, or use something like a global counter to name them uniquely, then when trying to re-apply any rules that referenced nodes created after the point of backtracking will fail, because those exact nodes no longer exist, even if nodes playing exactly the same role were created exactly the same way in the new branch.

To address this issue, we name nodes according to a hash of the rule and pattern assignment that produced them. Modulo hash collisions and applying the same rule to the same assignment twice, this makes node names commutative with the exact order of applying update rules and allows us to attempt the same rule assignment before and after a backtrack.

An alternative to this solution would be to explicitly keep information about the provenance of such generated nodes and refer to it when necessary. If such information is further stored in the structure itself, it could be used to perform MetaCat [49] style meta-reasoning, as discussed in Section 5.3.