A Framework for Assessing Decompiler Inference Accuracy of Source-Level Program Constructs

Keywords: Decompilers, Security

Abstract: Decompilation is the process of reverse engineering a binary program into an equivalent source code representation with the objective to recover high-level program constructs such as functions, variables, data types, and control flow mechanisms. Decompilation is applicable in many contexts, particularly for security analysts attempting to decipher the construction and behavior of malware samples. However, due to the loss of information during compilation, this process is naturally speculative and prone to inaccuracy. This inherent speculation motivates the idea of an evaluation framework for decompilers. In this work, we present a novel framework to quantitatively evaluate the inference accuracy of decompilers, regarding functions, variables, and data types. We develop a domain-specific language (DSL) for representing such program information from any "ground truth" or decompiler source. Using our DSL, we implement a strategy for comparing ground truth and decompiler representations of the same program. Subsequently, we extract and present insightful metrics illustrating the accuracy of decompiler inference regarding functions, variables, and data types, over a given set of benchmark programs. We leverage our framework to assess the correctness of the Ghidra decompiler when compared to ground truth information scraped from DWARF debugging information. We perform this assessment over all the GNU Core Utilities (Coreutils) programs and discuss our findings.

1 INTRODUCTION

In an increasingly digital world, cybersecurity has emerged as a crucial consideration for individuals, companies, and governments trying to protect their information, financial assets, and intellectual property. Of the many digital threats, various forms of malware continue to pervade the digital landscape. *Decompilation*, the translation from binary code into an approximate source-level representation, is a key strategy in attempting to understand the construction and behavior of malware samples. A *decompiler* is a program that performs decompilation. The decompilation process is inherently speculative and error-prone since high-level information such as function boundaries, variables, data types, and control flow mechanisms are lost during program compilation.

Due to this imprecise nature of decompilation, a generalized and extensible quantitative evaluation framework for decompilers is critical. Existing work (Liu and Wang, 2020) proposes an evaluation technique to determine whether decompiled programs, after recompilation, are consistent in behavior to their original binaries. Another work (Naeem et al., 2007) proposes a set of metrics for assessing the clarity of decompiled Java programs with respect to program size, conditional complexity, identifier complexity, number of local variables, and expression complexity. These works, although insightful for assessing decompiler quality, do not measure the recovery accuracy of high-level program constructs such as functions, variables, and data types. The recovery and inference of the these high-level constructs, in conjunction with clarity and behavioral correctness, is important to gain an understanding of decompiled binary programs.

Targeting the current gap in the literature, this paper presents a novel framework for quantifying and assessing the accuracy of decompiler tools with respect to high-level program constructs, including functions, variables, and data types. To validate our concept, we apply our framework to the Ghidra (National Security Agency (NSA), 2022) decompiler and discuss our findings. The primary objectives achieved by this work are as follows:

1. We define a domain-specific language (DSL), written in Python, for expressing high-level program information including functions, variables, and data types. This serves as a medium whereby we can translate program information extracted from a decompiler or a ground-truth source.
2. We employ our DSL to compare program representations from different sources. The primary use case is to compare ground-truth program information to that inferred by decompilers.
3. Leveraging the comparison logic in (2), we define

a set of quantitative metrics to measure the accuracy of function, variable, and data type inference.

4. We develop a translation module in Python that uses DWARF debugging information from a binary program to generate a ground-truth program information representation in our DSL.
5. We utilize the Ghidra Python API to implement a translation module from Ghidra's decompilation of a binary program to program information representation in our DSL.
6. Using our developed language, metrics, and translation modules, we quantitatively assess the accuracy of the Ghidra decompiler when compared to ground truth program information obtained from DWARF debugging information. We perform this analysis using the set of GNU Coreutils programs as benchmarks. We present the evaluation results and discuss additional findings and takeaways.

The remainder of this paper is outlined as follows: In Sections 2 and 3, we discuss background concepts and related research, respectively. Next, in Section 4, we detail our methodology for developing our evaluation framework. In Section 5, we present and discuss the results of applying our evaluation framework to the Ghidra decompiler. We conclude in Section 6 with a summary of our results and future research directions.

2 BACKGROUND

DWARF (DWARF Standards Committee, 2022) is a debugging file format used by many compilers and debuggers to support source-level debugging for compiled binary programs. When specified flags (usually '-g') are present at compilation, DWARF-supporting compilers such as GCC and Clang will augment the outputted binary program or object file with DWARF debugging information. A resulting binary executable can then be loaded into a DWARF-supporting debugger such as GDB to debug the target binary program with references to line numbers, functions, variables, and types in the source-level program. The DWARF standard is source language agnostic, but generally supports equivalent representations for constructs present in common procedural languages such as C, C++, and Fortran. In addition, DWARF is decoupled from any architecture or operating system. The generalizability of DWARF debugging information makes it a prime candidate for extracting "ground truth" information about a particular binary program, regardless of the specifics of the source language, architecture, or operating system. DWARF is leveraged in this work to obtain ground truth information about target binary programs.

Ghidra (National Security Agency (NSA), 2022), created and maintained by the National Security Agency (NSA) Research Directorate, is an extensible software reverse engineering framework that features a disassembler, decompiler, and an integrated scripting environment in both Python and Java. We use the Ghidra decompiler in this work to demonstrate our decompiler evaluation framework.

3 RELATED WORK

In a 2020 paper (Liu and Wang, 2020), the authors present an approach to determine the correctness of decompilers outputting C source code. They aim to find decompilation errors, recompilation errors, and behavior discrepancies exhibited by decompilers. To evaluate behavioral correctness, they attempt to recompile decompiled binaries (after potential syntax modifications) and use existing dynamic analysis techniques such as fuzzing to find differences in behavior between the recompiled and original programs. The objective of our work differs as we aim to evaluate decompiler inference of high-level structures such as functions, variables, and data types.

A 2006 technical report (Naeem et al., 2007) proposes a set of metrics for assessing the "cognitive expressibility" (clarity) of decompiled Java code. This is achieved through metrics that capture program size, conditional complexity, identifier complexity, number of local variables, and expression complexity. Despite the importance of these aspects in assessing the quality of a decompiler, this approach does not consider the "correctness" - either behavioral or structural - of the decompiled code. In addition, this work only targets decompiled Java programs.

Several existing works propose methodologies and frameworks targeting high-level variable and type inference from binary programs (Balakrishnan and Reps, 2007; Lee et al., 2011; Caballero et al., 2012; Lin et al., 2010; ElWazeer et al., 2013; Noonan et al., 2016). Many of these works contain an evaluation of their inference accuracy; however, none of these works demonstrate evaluation metrics that express a unified assessment of function, variable, and data type recovery.

4 METHODOLOGY

In this section, we discuss the philosophy, design, and construction of our decompiler evaluation framework.

4.1 Domain-Specific Language (DSL) for Program Information

We develop a domain-specific language (DSL) in Python to represent program information such as functions, variables, data types, and addresses, as well as the relationships between them. This DSL acts as a bridge linking binary-level information with the source-level structures such as functions, variables, and data types. Our DSL is decoupled from the source of the program information. Any ground truth or decompiler source of program information can be translated into a *ProgramInfo* construct in this common language (see Figure 1) and subsequently analyzed or compared with another source of program information.

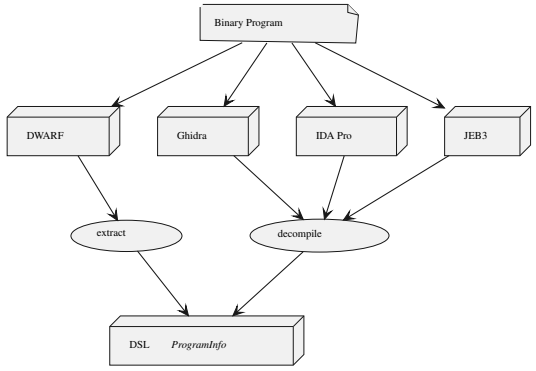


Figure 1: DSL *ProgramInfo* extraction from multiple *potential* sources (National Security Agency (NSA), 2022; Hex-Rays, 2022; PNF Software, 2022).

4.2 Capturing Ground Truth Program Information

With our DSL defined, we need a reliable method to extract "ground truth" information from a program and translate this information into our DSL. This ground truth information is intended to be used in a comparison with the program information obtained from a decompiler. Our framework is meant for evaluation and therefore we assume that we have access to the source code of benchmark programs used during evaluation.

Our approach to extracting ground truth program information involves leveraging debugging information optionally included in the binary by the compiler. The primary purpose of debugging information is to link binary-level instructions and addresses with source-level structures. We choose the DWARF debugging standard as the assumed debugging format for our framework; however, defining a translation module from another debugging format into our DSL is certainly possible. The DWARF debugging standard is supported by nearly all major Linux compilers and may be extended to support any source-level programming language. These properties of the DWARF standard allow it to be used as a "ground truth" source of program information, decoupled from the source language or the compiler.

To capture DWARF information from a given source program, we first compile the source program with the option to include debugging symbols. After we compile the program, we then extract the DWARF debugging information from the resulting binary. We utilize the *pyelftools* Python library (Bendersky, 2022) to perform this extraction. The extraction results in, among other information, a set of debugging information entries (DIEs). Together, these DIE records provide a description of source-level entities such as functions, variables, and data types in relation to low-level binary information such as program counter (PC) addresses and storage locations. Using this parsed DWARF information, we define a module that translates the DIEs into the equivalent constructs in our DSL.

4.3 Capturing Decompiler (Ghidra) Output Information

In addition to capturing a ground-truth program representation in our DSL, we must construct a DSL representation of the program information obtained from a decompiler we wish to evaluate. Depending on the decompiler and the structure of its output, this process may take many forms, often involving querying APIs exposed by the decompiler framework. In all cases however, this shall involve defining a translation module from the decompiler output to the constructs defined in the DSL.

For our analysis of the Ghidra decompiler, we utilize the Ghidra scripting API to programmatically scrape and process information about the decompilation of target binary programs. The Ghidra scripting environment exposes its own collection of data structures and functions from which we obtain our information.

The strategy employed for the Ghidra translation is similar to that of our DWARF translation algorithm. We utilize the Ghidra API to obtain particular information about functions, variables, data types, and associated addresses gathered during the decompilation, and subsequently translate this information into the structure of our DSL. Of particular use to our translation logic is the *DecompInterface* interface exposed by the Ghidra API.

4.4 Comparison of Ground Truth and Decompiler Program Information

With the ability to convert ground truth and decompiler (Ghidra) program information into our DSL, we formulate and implement a strategy to compare the two resulting *ProgramInfo* objects. To achieve this, we create an extension of our DSL that defines data structures and functions for capturing comparison information at different levels.

4.4.1 Data Type Comparison

Given two *DataType* objects and an offset between their start locations, we capture nuanced information about the comparison of the data types.

Definitions We define the *metatype* of a data type to be the general "class" of the given data type. These metatypes include *INT*, *FLOAT*, *POINTER*, *ARRAY*, *STRUCT*, *UNION*, *UNDEFINED*, *VOID*, and *FUNCTION_PROTOTYPE*. We consider *INT*, *FLOAT*, *POINTER*, *UNDEFINED*, and *VOID* to be *primitive metatypes* since they cannot be decomposed further. *ARRAY*, *STRUCT*, and *UNION* are considered *complex metatypes* since these types are formed via the composition or aggregation of different members or subtypes. We consider the 'char' data type to be of the *INT* metatype with size equal to one byte.

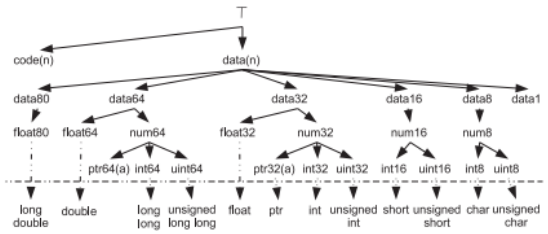


Figure 2: The ARTISTE type lattice (Caballero et al., 2012; Caballero and Lin, 2016).

A *primitive type lattice* (Caballero and Lin, 2016) is used to hierarchically relate primitive data types based on their metatype, size, and signedness (if applicable). More general types are located higher in the lattice while more specific types are located closer to the leaves. A type lattice may be used to determine whether two primitive data types are equivalent or share a common parent type. Our framework leverages a modified version of the ARTISTE primitive type lattice defined in Caballero et. al (Caballero et al., 2012) and shown in Figure 2.

We next define a *subset* relationship between two data types. For a given complex data type X and another data type Y with a given offset (possibly 0) between the location of X and Y in memory, Y is considered a *subset* type of X if Y is equivalent to a "portion" of X, consistent with the offset between X and Y. For example, if X is an array, any sub-array or element of X such that elements are aligned and the element types are equivalent to X is considered a subset of X. If X is a struct or union, any sub-struct or member with proper alignment and equal constituent elements is considered a subset of X.

Comparison Logic Suppose we have two *DataType* objects X (ground truth) and Y (decompiler) with offset k from the start of X to the start of Y. The goal is to compute the *data type comparison level* for the given comparison. The possible values for the comparison level are as follows, from lowest equality to highest equality:

- *NO_MATCH*: No relationship could be found between X and Y.
- *SUBSET*: Y is a subset type of complex type X.
- *PRIMITIVE_COMMON_ANCESTOR*: In the primitive type lattice, Y is an ancestor of X. This indicates that the inferred type Y is a conservative (more general) form of the ground truth type X.
- *MATCH*: All properties of X and Y match including metatype, size, and possibly subtypes (applicable to pointers, arrays, structs, and unions).

We first check the equality of X and Y. If X and Y are equal, we assign the *MATCH* comparison code. In the case that X and Y are both primitive types, we attempt to compute their shared ancestor in the primitive type lattice. If Y is an ancestor (more general form) of X, we assign *PRIMITIVE_COMMON_ANCESTOR*. If X is a complex type, we employ an algorithm to determine whether Y is a subset of X at offset k by recursively descending into constituent portions of X starting at offset k (substructs, sub-arrays, elements, members) and checking for equality with Y. If a subset relationship is found, we assign the *SUBSET* compare level. In all other cases, we assign the *NO_MATCH* compare level.

4.4.2 Variable (Varnode) Comparison

There are two main contexts where variable comparison occurs. The first context is at the top level, where the set of ground-truth global variables is compared to the set of decompiler global variables. The second context for variable comparison is within the context of a function when we compare local variables between the ground-truth and the decompiler. In either case, comparing sets of variables starts with the de-

composition of each *Variable* object from the DSL into a set of *Varnode* objects in our extended DSL.

A *Varnode* ties a *Variable* to a specific storage location and the range of PC addresses. The varnodes for a given variable are directly computed from the variable's live ranges discussed previously. In unoptimized binaries, it is the case that a single *Variable* shall decompose into a single *Varnode*.

With each variable decomposed into its associated varnodes, we next partition the varnodes from the ground-truth information and the decompiler based on the "address space" in which they reside. These address spaces include the *absolute* address space, the *stack* address space, and the *register offset* address space (for a given register). The *stack* address space is a special case of the *register offset* address space where the offset register is the base pointer which points to the base of the current stack frame.

For the set of varnodes in each address space, we first order them based on their offset within the address space. Next, we attempt to find overlaps between varnodes from the two sources based on their location and size. If an overlap occurs between two varnodes, we compute a data type comparison taking into account the offset between the start locations of the two varnodes. The data type comparison approach is described in the previous section. Based on the overlap status and data type comparison of a ground-truth varnode X, one of the following *varnode comparison levels* are assigned (see Figure 3):

- *NO_MATCH*: X is not overlapped with any varnodes from the other source.
- *OVERLAP*: X overlaps with one or more varnodes from the other space, but the data type comparisons are level *NO_MATCH*.
- *SUBSET*: X overlaps with one or more varnodes and each of its compared varnodes has data type comparison level equal to *SUBSET*. In other words, the compared varnode(s) make up a portion of X.
- *ALIGNED*: For some varnode Y from the other source, X and Y share the same location and size in memory; however, the data types of X and Y do not match. The data types comparison could have any comparison level less than *MATCH*.
- *MATCH*: For some varnode Y from the other source, X and Y share the same location and size in memory, and their data types match exactly.

The inference of variables with complex data types including structs, arrays, and unions proves to be a major challenge for decompilers. Recognizing this, we develop an approach to compare the sets of

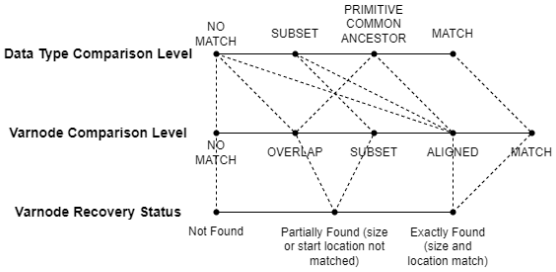


Figure 3: The derivation of varnode comparison level from varnode recovery status and data type comparison.

ground truth and decompiler variables (varnodes) in their most "decomposed" forms. An analysis of this sort helps to recognize how well a decompiler infers the primitive constituent components of complex variables. Furthermore, this allows us to recognize the aggressiveness and accuracy of complex variable synthesis from more primitive components.

Our approach to recursively decompose complex types into their primitive components is illustrated in Figure 4. We first implement an approach to recursively strip away the "complex layers" of a varnode to its most primitive decomposition. This primitive decomposition produces a set of one or more primitive varnodes as they would appear in memory. For example, an array of elements is broken down into a set of its elements (decomposed recursively). A struct is broken down into a set of varnodes associated with each of its members (decomposed recursively). Unions present a special case since the members share a common, overlapping region of memory. Hence, to decompose a union, we transform it into an *UNDEFINED* primitive type with the same size as the union.

We apply this primitive decomposition to each varnode in the sets of ground truth and decompiler varnodes. With the two sets of decomposed varnodes, we leverage the same variable comparison approach described previously to compare the varnodes in these sets. The resulting comparison information is treated as a separate analysis from the unaltered varnode sets.

4.4.3 Function Comparison

The first step in function comparison is to determine whether each ground-truth function is found by the decompiler. We first order the functions from each source by the start PC address of the function. Next, we attempt to match the functions from the two sources based on start address. Any functions from the ground-truth that are not matched by a decompiler function are considered "missed". For any missed functions, we consider its associated parameters, local variables, and data types to also be "missed".

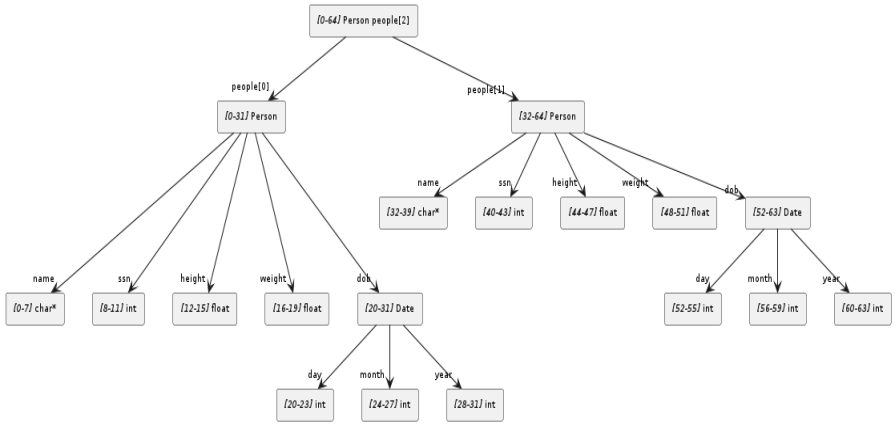
For each *matched* function based on start PC ad-

```
typedef struct {
    int day;
    int month;
    int year;
} Date;

typedef struct {
    char* name;
    int ssn;
    float height;
    float weight;
    Date dob;
} Person;

Person people[2];
```

(a) The definition of a high-level variable.



(b) The decomposition of a high-level varnode into primitive components.

Figure 4: An example of the recursive decomposition of a high-level varnode.

dress, we compute and store information including the return type, parameter, and local variable comparisons. These sub-comparisons leverage the data type and variable (varnode) comparison techniques described previously.

5 EVALUATION

To demonstrate our evaluation framework, we target the Ghidra decompiler (version 10.2). We use all 105 GNU Core Utilities programs (version 9.1) as our set of benchmarks. For each of the benchmark programs, we evaluate the accuracy of Ghidra decompilation with the program compiled in three ways: (1) stripped, (2) standard (not stripped, no debugging symbols), and (3) DWARF debug symbols included. We use the results from each of these cases to discern how the amount of information included in the binary affects the Ghidra decompiler's inference accuracy. To limit the scope of our analysis, we only consider *unoptimized* binaries. We use the GCC compiler (version 11.1.0) to compile the benchmark programs. The architecture and operating system of the testing machine are x86-64 and Ubuntu Linux (version 20.04), respectively. Figure 5 illustrates our process for gathering evaluation metrics on an individual benchmark program under each of the compilation conditions.

5.1 Function Recovery

Table 1 summarizes of the function recovery statistics accumulated over all benchmark programs. We find

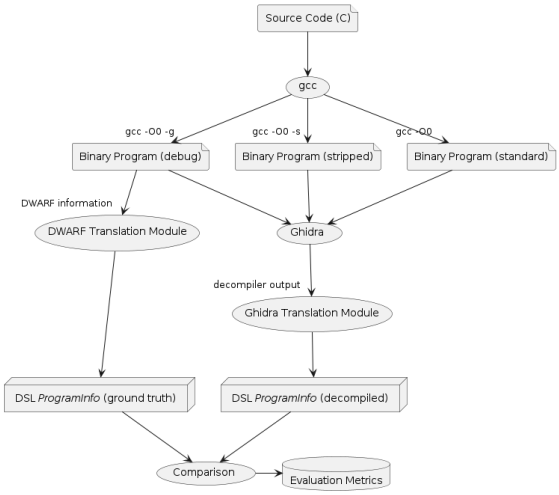


Figure 5: The process used to gather evaluation metrics on the Ghidra decompiler for a given benchmark program.

that over the 18139 functions present in the ground truth, the stripped and standard compilation cases produce 100% function recovery while the debug case fails to recover four functions, resulting in a 99.9% recovery rate. Upon further examination, we find that all four functions missed are from the *factor* program.

Table 1: Function recovery by compilation case.

	Ground truth	Functions found	Functions missed	Recovery fraction
strip	18139	18139	0	1.0000
standard	18139	18139	0	1.0000
debug	18139	18135	4	0.9998

To determine the cause of the missed functions, we further investigate the Ghidra decompilation of *factor* and find that each of the missed functions results in a decompilation error, "Low-level Error: Unsupported data-type for ResolveUnion". This indicates that an error occurred when attempting to resolve a union data type within the decompilation of these functions. Since this error only occurs in the debug compilation case, it is clear that Ghidra's parsing and interpretation of DWARF information contributes to this error. This same union data type causing the error is successfully captured and represented in our ground truth program information and, thus, this is likely a bug within Ghidra's resolution logic.

5.2 High-Level Variable Recovery

To evaluate the variable (varnode) recovery accuracy of the Ghidra decompiler, we first measure the inference performance of high-level varnodes, including varnodes with complex and aggregate types such as arrays, structs, and unions. We further measure the varnode inference accuracy by metatype to decipher which of the metatypes are most and least accurately inferred by the decompiler. This analysis is performed under each compilation configuration (stripped, standard, and debug).

In all our varnode evaluation tables, the *Varnode comparison score* metric is defined as follows: For each *varnode comparison level*, we first linearly assign an integer representing the strength of the varnode comparison (*NO_MATCH* = 0, *OVERLAP* = 1, *SUBSET* = 2, *ALIGNED* = 3, *MATCH* = 4). We then normalize these scores to fall within the range zero to one. Then, for each ground truth varnode, we compute this normalized score. We take the average score over all ground truth varnodes to obtain the resulting metric. This metric approximates how well, on average, the decompiler infers the ground truth varnodes.

In Table 2, we show the high-level varnode recovery metrics for each of the compilation conditions, aggregated from each of the benchmark programs. We find that Ghidra at least partially infers 97.2%, 99.3%, and 99.6% and precisely infers 36.1%, 38.6%, and 99.7% of high-level varnodes for each of the stripped, standard, and debug compilation cases, respectively. In addition, the varnode comparison scores for each compilation case are 0.788, 0.816, and 0.998, respectively. These metrics indicate that the standard compilation case slightly outperforms the stripped case in varnode inference while the debug compilation case results in significant improvements over both the stripped and standard cases, particularly in exact varnode recovery.

In Table 3, we show the inference performance of high-level varnodes broken down by the metatype for each compilation configuration. From the stripped and standard compilation cases, we observe that varnodes with metatype *INT* are most accurately recovered when considering *varnode comparison score*, *fraction partially recovered*, and *fraction exactly recovered*. In the stripped case, the inference of *ARRAY* varnodes shows the worst performance with a varnode comparison score of 0.315. In the standard case, varnodes with metatype *STRUCT* are least accurately recovered with a varnode comparison score of 0.560, followed closely by *ARRAY* and *UNION*. We see that, for both the stripped and standard compilation cases, the complex (aggregate) metatypes, *ARRAY*, *STRUCT*, and *UNION*, show the lowest recovery accuracy with respect to varnode comparison score. Among the primitive metatypes, *FLOAT* shows the worst recovery metrics for these two cases.

The debug compilation case demonstrates high relative recovery accuracy across varnodes of all metatypes when compared to the stripped and standard cases. Of the primitive metatypes, varnodes of the *FLOAT* metatype are perfectly recovered while varnodes of the *INT* and *POINTER* metatypes show exact recovery percentages of 99.8% and 99.9%, respectively. The complex (aggregate) metatypes, on average, display slightly lower recovery metrics than primitive metatypes in the debug compilation case. The *ARRAY* metatype reveals the worst varnode comparison score at 0.986. The *UNION* metatype demonstrates the lowest exact match percentage at 87.5%.

5.3 Decomposed Variable Recovery

In this section, we repeat a similar varnode recovery analysis over all varnodes; however, we first recursively decompose each varnode into a set of primitive varnodes (see Section 4). We perform this analysis over all benchmarks for all three compilation cases.

Similar to the high-level varnode analysis, we show the inference of the decomposed varnodes for each benchmark and for each compilation configuration in Table 4. Naturally, we expect to see lower recovery metrics compared to the high-level varnode analysis since each complex varnode is now analyzed as a set of its constituent parts. Hence, as a single "missed" high-level varnode is translated into a set of primitive varnodes, each of its constituent is "missed" in this analysis. As a result, all our scoring metrics, including the *varnode comparison score*, *varnodes fraction partially recovered*, and *varnodes fraction exactly recovered* show lower values than in the high-level analysis. We see that the decomposed

Table 2: A summary of high-level varnode recovery by compilation case.

	@Level NO_MATCH	@Level OVER-LAP	@Level SUBSET	@Level ALIGNED	@Level MATCH	Compare score	Partial recovery fraction	Exact recovery fraction
strip	1000	1662	1001	18570	12550	0.788	0.971	0.361
standard	249	1450	613	19029	13442	0.816	0.993	0.386
debug	23	52	24	7	34677	0.998	0.999	0.997

Table 3: A summary of high-level varnode recovery by compilation case and metatype.

		@level NO_MATCH	@level OVER-LAP	@level SUBSET	@level ALIGNED	@level MATCH	Compare score	Partial recovery fraction	Exact recovery fraction
strip	INT	66	48	0	12204	8681	0.850	0.997	0.413
	FLOAT	0	56	0	113	22	0.632	1.000	0.115
	POINTER	53	4	0	5834	3513	0.839	0.994	0.374
	ARRAY	729	597	565	19	228	0.315	0.659	0.107
	STRUCT	152	955	432	390	106	0.419	0.925	0.052
	UNION	0	2	4	10	0	0.625	1.000	0.000
standard	INT	23	48	0	12248	8680	0.851	0.999	0.413
	FLOAT	0	56	0	113	22	0.632	1.000	0.115
	POINTER	44	4	0	5836	3520	0.840	0.995	0.374
	ARRAY	181	578	352	45	982	0.625	0.915	0.459
	STRUCT	1	762	257	777	238	0.560	1.000	0.117
	UNION	0	2	4	10	0	0.625	1.000	0.000
debug	INT	13	27	0	4	20955	0.998	0.999	0.998
	FLOAT	0	0	0	0	191	1.000	1.000	1.000
	POINTER	3	0	0	1	9400	1.000	1.000	1.000
	ARRAY	5	17	24	0	2092	0.986	0.998	0.978
	STRUCT	2	8	0	0	2025	0.996	0.999	0.995
	UNION	0	0	0	2	14	0.969	1.000	0.875

varnode comparison scores for the strip, standard, and debug compilation cases are 0.586, 0.703, and 0.980, respectively. The varnodes fraction partially recovered are 73.8%, 92.5%, and 98.0% while the varnodes fraction exactly recovered are 24.7%, 25.0%, and 98.0% across the compilation cases, respectively. Interestingly, in the stripped compilation case, we find that the number of "missed" decomposed varnodes (139937) exceeds the number of "exactly matched" decomposed varnodes (131719). This is largely due to the quantity of high-level *ARRAY* and *STRUCT* varnodes that are missed in the stripped case.

We partition the decomposed varnodes by metatype and show these results in Table 5. The table shows that the stripped and standard compilation cases demostrate the poorest inference performance in terms of varnode comparison score for varnodes of metatype *FLOAT*. However, we find that the percentage of "missed" *INT* varnodes is worse than that of *FLOAT* in the standard and debug compilation cases, and is nearly the same in the stripped case. This may be explained by the prevalence of integer (or character) arrays in the Coreutils benchmark programs when compared to other array types. Recovery accuracy of the *POINTER* metatype is comparable to the *INT* metatype across the three compilation cases.

5.4 Data Bytes Recovery

Following from our varnode inference analysis, we next assess the accuracy of the Ghidra decompiler with regards to the total number of data bytes recovered across all varnodes. This analysis provides an important perspective on data recovery as we can now correctly account for the *size* of an improperly inferred varnode. For example, a large array and a single character are each represented by a varnode, but the quantity of data present in the array is often much greater than that of a character. Hence, it is important to capture this nuanced view of data recovery.

In Table 6, we show the aggregated data bytes recovery metrics across the benchmarks for each com-

Table 4: A summary of decomposed varnode recovery by compilation case.

	@Level NO_MATCH	@Level OVER-LAP	@Level SUBSET	@Level ALIGNED	@Level MATCH	Compare score	Partial recovery fraction	Exact recovery fraction
strip	139776	31280	0	231267	131593	0.586	0.738	0.246
standard	40187	56605	0	303527	133597	0.703	0.925	0.250
debug	10547	128	0	5	523236	0.980	0.980	0.980

Table 5: A summary of decomposed varnode recovery by compilation case and primitive metatype.

		@level NO_MATCH	@level OVER-LAP	@level SUBSET	@level ALIGNED	@level MATCH	Compare score	Partial recovery fraction	Exact recovery fraction
strip	INT	132910	28812	0	217923	125159	0.586	0.737	0.248
	FLOAT	72	73	0	103	22	0.435	0.733	0.081
	POINTER	6725	2057	0	13208	6332	0.591	0.763	0.224
standard	INT	40017	46846	0	290436	127505	0.707	0.921	0.253
	FLOAT	0	145	0	103	22	0.502	1.000	0.081
	POINTER	132	9245	0	12955	5990	0.636	0.995	0.211
debug	INT	10533	124	0	4	494143	0.979	0.979	0.979
	FLOAT	0	0	0	0	270	1.000	1.000	1.000
	POINTER	14	2	0	1	28305	0.999	1.000	0.999

Table 6: A summary of data bytes recovery.

	Ground truth	Bytes found	Bytes missed	Recovery fraction
strip	1183691	725144	458547	0.613
standard	1183691	954105	229586	0.806
debug	1183691	1177221	6470	0.995

pilation case. We see that Ghidra recovers 61.3%, 80.6%, and 99.5% of data bytes in the stripped, standard, and debug compilation cases, respectively.

5.5 Array Inference Accuracy

The last major analysis we perform targets the array inference accuracy of the Ghidra decompiler. We aim to measure the total number of arrays inferred, the length and size discrepancies, and the similarity of element types of compared arrays. The descriptions of the metrics are as follows:

- *Ground truth varnodes (metatype=ARRAY)*: The number of ground truth varnodes with metatype of ARRAY.
- *Array comparisons*: The number of array comparisons made when comparing the ground truth with the decompiler. The decompiler may infer 0 or more array varnodes for each given ground truth array varnode.
- *Array varnodes inferred as array*: This measures how many ground truth array varnodes are compared to at least one decompiler-inferred array varnode.
- *Array varnodes inferred as array fraction*: Equivalent to *Array varnodes inferred as array* divided by *Ground truth varnodes (metatype=ARRAY)*. This expresses the fraction of ground truth array varnodes that are associated with at least one decompiler array inference.
- *Array length (elements) average error*: For each array comparison, we find the absolute difference in the number of elements inferred by the decompiler as compared to the ground truth. We then average these differences over all array comparisons to arrive at this metric.
- *Array length (elements) average error ratio*: For each array comparison, we first find the absolute difference in the number of elements inferred by the decompiler as compared to the ground truth. We then divide this error by the length of the ground truth array to get the error as a ratio of the array size. The average of these ratios over all array comparisons produces this metric.
- *Array size (bytes) average error*: This metric is similar to *Array length (elements) average error* but measures the error in bytes instead of number of elements.
- *Array size (bytes) average error ratio*: This metric is similar to *Array length (elements) average error*

ratio but computes the error in bytes instead of array elements.

- *Array dimension match score*: This metric is the number of array comparisons where the decompiler inferred the correct number of dimensions divided by the total number of array comparisons.
- *Array average element type comparison score*: Each *data type comparison level* is first mapped to an integer as follows: *NO_MATCH* = 0, *SUBSET* = 1, *PRIMITIVE_COMMON_ANCESTOR* = 2, *MATCH* = 3. We then normalize these values such that the range is scaled from 0 to 1. We refer to this as the *data type comparison score*. Then, for each array comparison, we compute the *data type comparison score* and subsequently average the scores across all array comparisons to generate this metric.

We perform our analysis across all our benchmarks and for each compilation configuration, resulting in the data presented in Table 7.

Across all benchmarks, there are 2138 ground truth arrays present. For each of the stripped, standard, and debug compilation cases, the number of ground truth arrays recognized as arrays by the decompiler are 774 (36.2%), 1530 (71.6%), and 2128 (99.5%), respectively. We see that the numbers of array comparisons for each compilation case are greater than these metrics indicating that Ghidra infers some ground truth arrays to be more than one array.

From the array comparisons, we observe that the average absolute differential in array length (number of elements) for the stripped, standard, and debug compilation cases are 134.7, 151.2, and 9.4, respectively. When scaling these errors with respect to the length of the ground truth arrays in the comparisons, the error ratios are 2.84, 5.44, and 0.11 for the compilation cases, respectively. This reveals that, in the debug case for example, the lengths of decompiler-inferred arrays are off by an average of 9.4 elements and roughly 11% (greater or less than) of the size of the ground truth arrays they are compared to. These metrics, however, fail to capture whether the decompiler-inferred array has element types of the correct length. Thus, a similar analysis on the size (number of bytes) errors yields errors and error ratios of 458.6 (0.91), 239 (0.47), and 9.41 (0.11) for each compilation case, respectively. This, for example, shows that arrays inferred in the standard compilation case have an average absolute byte differential of 239 and a relative error of 47% compared to the size of the ground truth array they are compared to.

In this analysis, we also capture a measure of the array dimension match score for each compilation case. This metric measures the fraction of array comparisons where the decompiler-inferred array has the same dimensionality (one-dimensional, two-dimensional, etc.) as the ground truth array. The stripped and standard compilation cases display dimensionality match ratios of greater than 97.4%, while the debug case shows 100% dimensionality inference accuracy.

The last portion of our array recovery analysis focuses on the element type inference accuracy of the decompiler-inferred arrays when compared to the element types of the ground truth arrays. We compute a data type comparison score between the element types from each array comparison and average these across all array comparisons derived from our benchmark programs. This data type comparison score is similar in concept to the varnode comparison score and is described in Section 4. We find that decompiler-inferred arrays in the stripped, standard, and debug compilation cases show 0.781, 0.670, and 0.999 average element type comparison scores, respectively. The better performance demonstrated in the stripped case compared to the standard case appears to be a data artifact resulting from fewer array comparisons present in the stripped analysis.

5.6 Debug Compilation Case Discussion

Upon examination of our results, the reader may wonder why the debug compilation case does not produce 100% recovery for varnodes and data bytes across all benchmarks. The same DWARF information used to generate the ground truth program information is also provided to the Ghidra decompiler in this case and therefore, theoretically, Ghidra should be able to precisely capture the same program information.

We explore the causes of misses and partial misses in the debug case across the benchmark programs and find that Ghidra possesses a major limitation in expressing local variables declared in lexical scopes below the top level of a function. A compiler such as GCC may reuse stack address space for variables associated with disjoint (non-overlapping and non-nested) lexical scopes. This is a problem for the Ghidra decompiler as we observe that all variable declarations are placed at the top level of the function, ultimately preventing these scope-specific variables from being precisely captured. From our manual analysis of the decompiled benchmark programs, we find that this is the cause of the majority of partially missed variables and data bytes in the debug compilation case. This limitation affects the stripped and standard compilation cases as well. We consider this to be a shortcoming and an area of future improvement for the Ghidra decompiler.

Table 7: A summary of array recovery by compilation case.

	Ground truth array varnodes	Array comparisons	Array varnodes inferred as array	Array varnodes inferred as array fraction	Array length (elements) average error	Array length (elements) average error ratio	Array size (bytes) average error	Array size (bytes) average error ratio	Array dimension match score	Array average element type comparison score
strip	2138	823	774	0.362	134.695	2.845	458.575	0.912	0.979	0.781
standard	2138	1579	1530	0.716	151.156	5.442	239.023	0.475	0.975	0.670
debug	2138	2226	2128	0.995	9.416	0.110	9.416	0.110	1.000	1.000

6 CONCLUSION

In this work, we develop a novel framework for evaluating decompiler tools based on the recovery accuracy of high-level program constructs, including functions, variables, and data types. This framework includes a domain-specific language (DSL), developed in Python, to represent and compare sources of high-level program information and their association with binary-level information. In addition, we devise quantitative metrics for expressing the recovery accuracy of high-level program constructs. We leverage our framework to perform an in-depth evaluation of the Ghidra decompiler with respect to high-level function, variable, and data type recovery. This evaluation is performed over the GNU Core Utilities programs under three compilation conditions. We also discover and discuss the implications of two key issues present in the Ghidra decompiler.

In future work, we will extend our framework to support the evaluation of optimized binary programs. We also plan to develop techniques to evaluate behavioral correctness and overall clarity of decompiler output (Liu and Wang, 2020; Naeem et al., 2007). Finally, we will use our framework to analyze and compare other decompilers.

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